ESSAYS ON STRUCTURAL ANALYSIS OF RETAIL COMPETITION USING CLASSICAL AND BAYESIAN ESTIMATION TECHNIQUES

A Dissertation

Presented to the Faculty of the Graduate

of Cornell University

In Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

Sriraman Venkataraman

January 2005

ESSAYS ON STRUCTURAL ANALYSIS OF RETAIL COMPETITION USING CLASSICAL AND BAYESIAN ESTIMATION TECHNIQUES

Sriraman Venkataraman, Ph. D.

Cornell University 2005

The thesis is a collection of three essays on retail competition that are relevant to both the theory and practice of marketing. Essay 1, examines the role of price and category assortment on competition between EDLP (Every Day Low Price) format and HILO (Promotion) format retail stores. Policy experiments are conducted to study the strategic implications of 1) retail assortment reduction and 2) customized (household specific) coupons. The empirical analysis is conducted using a) household and store level scanner data and b) combination of hierarchical Bayes and classical estimation techniques.

Essay 2, models the price and geographic location elements of consumer demand, firm costs and competition in the lodging industry. A new demand model (Heterogeneous Aggregate Generalized Nested Logit) is introduced. The essay demonstrates the role of geographic location as an important element of retailers' marketing mix. Essay 3, proposes an empirical framework for long-run discrete dynamic games to study market firm's entry, stay, and exit decisions in the lodging market. The econometric model is based on Markov perfect equilibrium concept and relies on dynamic programming computational techniques. Essays 2 and 3 use aggregate data and classical estimation techniques to recover the underlying structural parameters.

BIOGRAPHICAL SKETCH

Sriram began his doctoral studies at Cornell University in Fall 2000. He has received undergraduate and graduate degrees in engineering and management. Prior to his stint at Cornell, Sriram worked in research and development divisions at Sun Microsystems Inc. and Apple Computers Inc. in California, USA. He holds patents in systems and computer networking and begins his teaching career as an Assistant Professor of Marketing at the Goizueta Business School at Emory University in Fall 2004.

To

Daddy

and

Amma

ACKNOWLEDGMENTS

No duty is more urgent than that of returning thanks.

~ St. Ambrose ~

While this dissertation bears my name, it is in truth an outcome of the joint effort of many. The list of people I ought to acknowledge is endless. I take this opportunity to high-lighten the role of some.

First, my dissertation co-chairs Professors Sachin Gupta and Vrinda Kadiyali. They have been both phenomenal mentors and dear friends. I am in awe of their patience, perseverance, modesty and intellect. Had it not been for their guidance and encouragement, this thesis would have continued to be a fragment of my imagination. My apologizes for the zillion hours that I used up of their time discussing potential research ideas. A typical meeting would start with me walking into their office having had a EUREKA moment and proposing what I deemed a 'GREAT DISSERTATION TOPIC'. By the end of such a meeting, I would walk away convinced that the idea was uninteresting at best, prompting reading for the next GREAT PROBLEM and meeting. You know how the rest goes.

These meetings helped me get a better understanding of the material and reinforced my belief in their mastery of their research areas. Advisors, I thank you and your family for being there for me during both the good (low frequency event) and bad (high frequency event) times. I look forward to much more productive research collaborations with you in the years to come.

I thank Professor Vithala R. Rao for mentoring me through various stages in the doctoral program. This thesis has benefited significantly from the depth and breadth of his knowledge. Thank you for your commitment to my research training and for presenting me with the opportunity to be part of the intellectually charged Cornell community.

I have also benefited greatly from my discussions with Professor Robert T. Masson, whose regulatory expertise and insights added both institutional and policy insights to my work.

I thank Professor Pradeep Chintagunta, for encouraging me to pursue a degree in marketing and for his continued advice and encouragement. I would also like to thank Cornell alums like K. Sudhir, Seethu Seetharaman and Bill Putsis for convincing me that Cornell's doctoral program was the ideal one for me. You were right, it is.

However none of this could have been possible without the unconditional love and support of my family. Dad and Amma, thank you for making numerous personal and professional sacrifices so that I can realize my dreams. Thank you for being there for me whenever I need you and for offering a patient ear to my complaints about mostly petty things. Your love has and will continue to be a great source of strength to me during the good and bad times. Please accept the dedication of this thesis to you, as a very small token of my love and admiration for you.

Kitta, thank you for being such a caring brother and friend. Thanks for patiently listening to my numerous and often repetitious ramblings about the world of marketing research. Thank you also for taking such great care of amma and dad while I plugged away on what you perceive are “worthless economic models”. Since I haven’t been successful in convincing you till date, I hope that your interactions with the faculty members at Cornell as you begin your graduate studies here, gets you to appreciate the theoretical underpinnings of what I have set out to do for a living.

I thank Esther for bearing with my long one-way chatters about the econometrics of demand modeling, consumer heterogeneity and Bayesian estimation. Not to mention my run down of who made tenure where -- in how many years -- with how many A hits, or who received a chaired position before he/she could learn to walk upright. Thank you for giving me hope when I was emotionally down and making sure that I never gave up without putting up a good fight.

I thank my dear friend Sudheer Chava for patiently sitting through me whining about my non-converging GAUSS code and for giving me false hope in my abilities. Other noteworthy contributors include my fellow doctoral students especially Ben Kartono, Meng Su, Natalia Golovashkina, Alfredo Mendiola, Amiyatosh Purnanandam, Rajesh Shah and Dobrina Teifel. I would also like to thank the incredible occupants of room 304 in particular Colleen Holman, Cathy Wetterer, Charlotte Mosher and Betty Conger for offering the best administrative support there is, not to mention filling me in on when and where free food was being served.

For the others who I haven’t identified I offer my sincere apologies and thank you from the bottom of my heart.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ESSAY 1

PRICE-ASSORTMENT LINKS IN CONSUMER AND COMPETITIVE CHOICES – A STRUCTURAL ANALYSIS OF RETAIL COMPETITION[1]

Abstract

In retailing, consumers may find their needs satisfied by either a single retailer or divide their patronage among multiple retailers who, in combination, satisfy their needs. This is particularly true in U.S. grocery retailing, where an overwhelming majority of consumers shop in more than one store (Progressive Grocer, 1997). The outcome of this is that retail stores compete for customers. Retail competition affects category pricing, assortment, promotion, store location and other decisions made by retailers. These decisions are based on retailers' perceptions of consumer demand, i.e. how consumers choose between retail stores, decide to purchase in categories in these stores, and choose brands/SKUs in these categories. Previous consumer demand focused studies that have modeled these three consumer choice decisions have done so ignoring the supply side interactions between competing retailers and/or have not modeled the three consumer choice decisions via a single utility maximization framework.

[1] The author acknowledges Professors Ram Rao, Young-Hoon Park, Ambar Rao, Chakravarti Narasimhan, and Eric Eisenstein for their insightful comments and Marketing Seminar attendees at Cornell University, Hong Kong University of Science and Technology, Emory University, University of Maryland, University of Texas at Dallas, University of Texas at Austin, Indiana University, University of British Columbia, Washington University at St. Louis and University of Pittsburgh for their comments and pointers. The author thanks David R. Bell for providing the IRI shopping basket data. The usual disclaimers apply.

On the supply side, theoretical literature on retail pricing recognizes (1) manufacturers' actions (e.g., wholesale prices, promotional payments) and (2) retail competition, as important drivers of retailer category pricing decisions. However, empirical studies have mainly studied manufacturer-level or multi-manufacturer-single-retailer competition. Effects of retail competition on retailer category pricing decisions have not received as much attention. The few studies that have either directly or indirectly accounted for the effect of retail competition on retailer category pricing decisions have not simultaneously modeled the three consumer decisions of store choice, category incidence and SKU choice. This limits one's understanding of the effects of retailers' decisions on the three consumer choice decisions. For example -- Does lowering prices increase store traffic or/and does it affect category incidence and SKU choice decisions? Are these effects similar across HILO and EDLP stores? Retailer category pricing decisions are based on retailers' perceptions of competitive responses to their own decisions. In turn, consumer choices are affected by these retail decisions. Therefore, to understand retail category pricing decisions, it is important to develop a joint framework of consumer choices across stores and brands/SKUs, and retailers' competitive decisions of prices, assortment, etc. that impact consumer choices. In this paper we build such a model of consumer choice and retail competition and their effect on retailer category pricing decisions.

By building on previous studies, we add to the current literature in important ways. We propose a unified utility structure that nests the three decisions of store choice, category purchase incidence and SKU choice. Our approach, therefore, allows for interdependencies in the three consumer choice decisions that have not been accommodated in previous studies. Unlike previous structural studies that have indirectly accounted for retail competition using aggregate data, we use actual marketing mix variables in competing stores to directly account for retail competition and estimate our proposed demand model using household level scanner panel data. By exploiting the panel structure of the data and accounting for consumer heterogeneity, we present a clearer understanding of household choices than studies using only aggregate data.

In addition to the usually studied marketing-mix variables of price, feature and display, we also study the role of retail category assortments -- assortment breadth (number of SKUs in category) and assortment depth (number of SKUs of each brand) -- in the consumer choice process. We also control for potential endogeneity in price and assortment. Rather than relying on classical estimation techniques, we estimate our model using the hierarchical Bayes procedure, which helps us recover household level parameters. A novel feature of this approach is that it allows retailers to identify households that might be more sensitive than others to retailers' category level decisions. On the supply side, we study category level retail competition by specifying a Bertrand-Nash pricing game between competing retailers. We estimate the resulting equilibrium pricing equations to obtain weekly retailer markups at the store-SKU level.

The proposed equilibrium model and the recovered demand and supply side estimates are used to address important questions about retail competition such as: a) What tradeoffs do consumers make in price and assortments? Are consumers willing to pay more for larger assortment depth or assortment breadth? b) How does assortment reduction affect retailer profits? Does assortment reduction affect retailers equally? c) What are the implications for retailer profits when retailers issue targeted coupons? Are these effects different for EDLP and HILO stores?

The model and estimates provide insights into the existence and magnitude of retail competition in price, and the effect of assortment depth and breadth on this competition. The proposed equilibrium model, i.e., the unified utility structure coupled with the supply model, provides a general framework to study a hierarchical consumer choice process and its implications for competition.

1. Introduction

In retailing, consumers may find their needs satisfied by either a single retailer or divide their patronage among multiple retailers who, in combination, satisfy their needs. This is more pronounced in U.S. grocery retailing, where research consistently shows that an overwhelming majority of consumers shop in more than one store (Progressive Grocer, 1997). The outcome of this is that retail stores compete for customers. Specifically, in the context of grocery retail, competition affects pricing, assortment, promotion, location and other decisions made by retailers. These decisions are based on retailers' perceptions of how consumers choose between retail stores, decide to purchase in categories in these stores, and choose brands/SKUs in these categories. Previous studies that have modeled these three consumer choice decisions have done so ignoring the supply side interactions between competing retailers and/or have not modeled the three consumer choice decisions via a single utility maximization framework.

On the supply side, the theoretical literature on retail category pricing recognizes (1) manufacturers' actions (e.g., wholesale prices, promotional payments) and (2) retail competition, as important drivers of retailer decisions (Lal and Villas-Boas, 1998; Pesendorfer, 2001). On the empirical side, some studies have explored other factors such as multi-category dependencies in retailer actions (Song and Chintagunta, 2003) and dynamics in retailer decisions within a category (Chen and Seetharaman, 2002). However, most empirical studies have assumed that retailers set prices for different brands/SKUs in a product category to maximize single period category profits (Raju, Sethuraman, and Dhar 1995; Tellis and Zufryden 1995; Chintagunta, 2002). In light of the emerging trend towards category management by retailers, this single category pricing decision/assumption might not be very restrictive (Zenor 1994). Among the empirical studies that have examined category pricing decisions, Chintagunta (2002) and Sudhir (2001) also examine departures from the standard category profit maximization assumption by a strategic retailer[2]. These departures might be a result of a retailer's favorability towards a certain brand or desire to increase the share of its private label.

Prior research suggests that in U.S. grocery retailing, retailers may react to activities at competing chains. The empirical evidence that relates prices and promotions in certain categories to store traffic is, however, mixed. Dhar and Hoch (1997) and Dreze (1995) suggest that retailers lower the prices of national brands to attract shoppers into the store. While Dreze (1995) finds that lower prices in the cola category attract more shoppers into the store, Walters (1991) and Walters and MacKenzie (1988) find that to be the case with some -- but not all -- brands within two focal categories.

---

[2] Store brand plays an important strategic role for the retailer (Dhar and Hoch,1997; Narasimhan and Wilcox,1998; and Scott--Morton and Zettelmeyer,2000). A retailer's favorability towards its private label can be motivated in part by the umbrella branding ability of the private label, and its resulting ability to build store loyalty. Retailers might receive special manufacturer deals or delegate the pricing decision to a channel captain. These effects might cause a retailer to deviate from its primary objective of maximizing category profits.

Despite theoretical findings that retail competition affects retailers' category pricing decisions, most structural empirical studies on retail category pricing have studied manufacturer-level or multi-manufacturer-single-retailer competition. Effects of retail competition on retailer category pricing decisions have not received as much attention. Furthermore, the few studies that have accounted for effects of retail competition on retailer category pricing decisions, have not simultaneously modeled the three consumer decisions (ex. Chintagunta, 2002).

Hence retail decisions can be based on retailers' perceptions of competitive responses to their own decisions. In turn, consumer choices are affected by these retail decisions. Therefore, to understand retail competition, it is important to develop a joint framework of consumer choices across stores and brands/SKUs, and retailers' decisions of prices, assortment, etc. that impact consumer choices. In this paper we build such a model of consumer choice and retail competition.

By building on previous studies, we add to the current literature in important ways. We propose a unified utility structure that nests the three decisions of store choice, category purchase incidence and SKU choice. Using household level transaction data, comprised of shopping trips made by households across multiple stores belonging to different chains, we estimate a nested logit demand model. Our specification, therefore, provides a framework in which the three consumer decisions are outcomes of the maximization of a *single* utility function. Therefore our approach allows for interdependencies in the three consumer choice decisions that have not been accommodated in previous studies. Unlike previous structural studies that have indirectly accounted for retail competition using aggregate data, we use the more preferred approach of using actual marketing mix variables in competing stores to directly account for retail competition and estimate our proposed demand model using household level scanner panel data. By exploiting the panel structure of the data and accounting for consumer heterogeneity, we present a clearer understanding of household choices than studies using only aggregate data.

In addition to the usually studied marketing-mix variables of price, feature and display, we also study the role of retail category assortments -- assortment breadth (number of SKUs in category) and assortment depth (number of SKUs of each brand) -- in the consumer choice process. We also control for potential endogeneity in price and assortment. Rather than relying on classical estimation techniques, we estimate our model using the hierarchical Bayes procedure, which helps us recover household level parameters. A novel feature of this approach is that it allows retailers to identify households that might be more sensitive than others to retailers' category level decisions. On the supply side, we study category level retail competition by specifying a Bertrand-Nash pricing game between competing retailers. We estimate the resulting equilibrium pricing equations to obtain weekly retailer markups at the store-SKU level.

To summarize, we account for both demand side and supply side factors (manufacturer prices and retail competition) that affect retailer category pricing via a structural equilibrium model. Thus, we build on the previous empirical literature on retailer pricing behavior and -- like Sudhir (2001) and Draganska and Jain (2002) -- focus on prices the retailer should charge conditional on the estimated demand and supply parameters.

The proposed equilibrium model and the recovered demand and supply side estimates are used to address important questions about retail competition such as:

1. How are retailers' profits affected by product line reduction by an upstream manufacturer? How are retailers' profits affected by assortment reduction by a retail account? Our equilibrium analysis considers the effects of reduced assortment on costs, sales, and margins of all competing retail stores.

2. What are the equilibrium implications of a targeted couponing strategy by retailers? Coupons enable firms to price discriminate between price-elastic and price-inelastic consumers (Narasimhan, 1984), thereby increasing firm profits. For example, Rossi and Allenby (1996) demonstrate that manufacturer profits from targeted coupons are as much as 2.5 times the profits from blanket coupon programs. Another view in the literature is that coupons reduce consumers' switching costs, thereby increasing price competition (Shaffer and Zhang, 1995; Bester and Petrakis, 1996) and reducing equilibrium profits. However, these papers have considered only the perspective of manufacturers. Our analysis provides empirical insights into the question of gains from targeted couponing by retailers.

   Besanko, Dube' and Gupta (2003) consider the profitability implications of targeted couponing in a market consisting of competing manufacturers who sell through a common retailer. However, this study ignores retail competition. In contrast, the current study assesses whether the market demand coupled with competitive retail conditions makes targeted price discrimination profitable for retailers. Specifically, does targeted couponing benefit all retailers or does it benefit some -- but not all -- retailers?

The model and estimates provide insights into the existence and magnitude of retail competition in price, and the effect of assortment depth and breadth on this competition. The proposed model -- i.e. the unified utility structure coupled with the supply model -- provides a general framework to study a hierarchical consumer choice process and its implications for competition.

2. Literature Review

In this section, we discuss three relevant streams of literature and how they relate to our analysis of retail competition.

2.1 Consumer choice modeling

There is a rich tradition of modeling consumer choice in marketing. Several papers in this area have examined how consumer decisions of store choice, category purchase incidence, and brand choice are influenced by retailer decisions. As our interest is in studying retail competition, we review papers that model store choice, the backbone of retail competition.

Bucklin and Lattin (1992) model consumer store choice, category purchase incidence, and brand choice decisions for laundry detergents. They do not find a significant effect of retail feature advertising on store substitution. However they do find that features affect category purchase incidence in a significant way. The category effect stems from consumers stockpiling when prices are low, which affects consumers' category purchase incidence probability in that store and other stores in the future. An important aspect of the model is that change in category purchase incidence does not alter the store choice probability because the store choice decision is modeled as being independent of the brand choice and category purchase decisions. The Bucklin and Lattin (1992) study accounts for observed consumer heterogeneity but not unobserved consumer heterogeneity. This may have caused bias in the estimated effects of marketing mix variables.

It appears likely that the assumption of independence of consumer decisions and unaccounted for consumer heterogeneity might have led to the finding that retailers' category marketing activity has no direct effect on consumer store choice. By this we mean that there might be a segment of consumers in the market whose store choice decisions are significantly influenced by retailers' category level marketing mix decisions, even though at the aggregate level these effects appear to be insignificant. This segment of store switchers can affect retailers' pricing decisions, especially if these consumers are also large basket shoppers. Hence we propose a unified econometric demand model that takes into account unobserved consumer heterogeneity to better control for the presence of retail competition.

Bell et al. (1998) and Bell and Lattin (1998) find that expected retail price of the shopping basket affects consumer store choice decisions. Hence retailers' pricing decisions across product categories affect consumer demand and retail competition.

While the Bucklin and Lattin (1992) single category analysis finds no evidence in support of retail competition, the Bell et al. (1998) and Bell and Lattin (1998) studies find empirical support for retail competition at the shopping basket level. The aim of the current study is to assess how retailer activity in a single category affects consumer store switching and retail competition. While previous studies have focused on the effects of marketing mix variables like price, feature advertising, merchandising etc., another variable in the retailers' marketing mix that affects store choice decisions is stores' assortment. We address the gap in the choice modeling literature by including this decision variable in the proposed consumer demand model.

2.2 Supply side modeling

Apart from the literature on choice models, there is also a complementary literature that focuses on competition, or supply side. We consider the following two studies in this genre. In a study of disposable diapers, Kumar and Leone (1988) use a hierarchical modeling approach to study pair-wise brand substitution effects both within and across stores. They find significant effects of price and features on store substitution. Walters' (1991) analysis of the cake mix and spaghetti sauce categories also finds evidence that single brand pricing activity in one store affects sales in competing stores. Since neither of these studies models consumer demand from a utility maximization perspective -- only aggregate sales -- their modeling framework is not suited to our goal of understanding the primitives of consumer choice of SKUs and stores, and therefore of retail competition.

2.3 Structural studies of competition

Building on both the choice literature and the supply side modeling literature, a third stream examines structural studies of competition. That is, they model consumer demand from utility maximization and competitive choices from profit maximization on the supply side (Kadiyali et al., 2001). Among the studies in this stream, literature on category management in grocery retail has explored competition between manufacturers, or between manufacturers and a common retailer (Besanko et. al.

1998, Sudhir 2001; Draganska and Jain 2001; Chintagunta 2002; Besanko et al. 2003). Issues of retail competition, however, have not received as much attention. The typical assumption in this literature is that the retailer engages in monopoly pricing. We address this gap in the literature by modeling competition among retailers.

To the best of our knowledge, BertoVillas-Boas (2002) is the only study to have directly modeled retail competition in the grocery industry based on an equilibrium structural demand-and-supply framework. BertoVillas-Boas (2002) studies vertical contracting in a channel setting using store level data. The use of aggregate data limits her from modeling the consumer store choice and category purchase incidence decisions. In a study of retailer category pricing strategies, Chintagunta (2002) uses a store traffic measure as a proxy for retail competition. Since he also uses aggregate data, the study faces the same limitations as Berto Villas-Boas (2002).

In contrast, our current study uses household level data, which enables us to model households' store choice, category incidence and SKU choice decisions. This allows us to gain additional insight into how retailer decisions affect various aspects of consumer behavior. Since our data contains competitors' marketing mix information, we do not rely on proxy measures of competition as in Chintagunta (2002). These features of our model provide a more comprehensive understanding than previous studies of how consumer demand and retail competition affect retailer category pricing.

Like the literature on choice models, the structural modeling literature has not studied the role of retail assortments on consumer choice, retailer costs or retailer category pricing. We address the gap in the structural modeling literature by including this variable in the proposed consumer demand model and the retailer cost specification. In addition, while accounting for retail competition we study how retailer assortments affect category-pricing decisions of competing grocery retailers.

2.4 Retail Assortments

Marketing management has stressed the importance of retailer product assortment in achieving differentiation and satisfying the wants of target shoppers better than the competition (e.g., Kahn, 1999; Kahn and McAlister, 1997). Levy and Weitz (1995) define assortment as "the number of different items in a merchandise category." While much of the empirical literature in marketing has focused on price and other marketing mix variables, retail assortment has received very limited attention. Like price, assortment has been found to be an important determinant of store profitability (Kahn and Schmittlein 1989, 1992).

1. ***Impact of Assortment on Consumer Demand (and hence Retail Revenues)***

   Consumers' store choice decisions are influenced by assortments offered (Kahn and Lehmann, 1991, Arnold et al. 1983). This is because the larger the selection, the more likely consumers are to find a product that matches their exact specifications (Baumol and Ide, 1956; Lattin and McAlister, 1985). A large assortment is particularly valuable for variety seeking consumers or consumers with uncertain preferences (Kahn and Lehmann 1991; Kahn 1995; McAlister and Pessemier 1982).

   Simonson (1999) shows that retail assortments can not only satisfy customers' wants, but also influence what they want. This suggests that a retailer's assortment decisions can change not only the likelihood that a consumer will make a purchase (category purchase incidence), but also affect the choice probability of a specific option (SKU choice).

2. Impact of Assortment on Retailer Costs

Assortment decisions also affect retailer costs. Questions such as how much space should be allocated to a category/brand/SKU within a category have been the main focus of the early work on cost implications of retail assortment (Corstjens and Doyle, 1981; Urban 1998). Retailers might also incur additional costs as a result of large assortments in the form of stock-outs and overstocking (van Ryzin and Mahajan, 1999), or as a result of maintaining consistent assortments (Krishnan et al. 2002).

3. Impact of Assortment on Competition

Focusing on the competitive drivers of assortment choice, Stassen et al. (1999) consider the retailer's assortment decision when consumers switch stores. A question that is very important to a retailer in this situation is whether he should differentiate from or mimic his competitor's assortment choice. Here category assortments can be thought of as another element of the retailer's marketing mix in attracting consumers into its store. Stassen's empirical results show that retailers mimic each other's assortments.

While results of these studies show sales increases with assortment size, anecdotal evidence suggests that retailers like Aldi and Save-a-Lot have managed to thrive by positioning themselves as low-service, low-cost, low-assortment players. These retailers serve a niche market of consumers who find a tradeoff of lower assortment for lower prices worthwhile. Thus store-level assortment (number of SKUs in category) and brand-level assortment (number of SKUs belonging to the same brand) may affect consumer shopping behavior, thereby affecting retailers' pricing and positioning strategy.

The McIntyre and Miller (1999) study considers both the demand side (consumer item choice) and the supply side (retailer item pricing and assortment composition decisions), while accounting for item complementarities and substitution for a category profit maximizing monopolist retailer. Unlike the McIntyre and Miller (1999) study, the focus of the current study is not the joint decisions of assortment selection and pricing. Instead we treat assortment decision (size of assortment, in our case) to be an exogenous decision, i.e. choice of assortment size is not being determined on a week-by-week basis. We focus on how retail category pricing is affected by a) the tradeoffs that consumers make in price and retail assortments while making SKU choice, category purchase incidence and store choice decisions, b) cost implications of retailer assortment, and c) regional competition. By simultaneously modeling the consumer, cost and competitive effects of retail assortments, our structural model serves as a useful tool for store managers to assess how assortment decisions affect equilibrium profits.

To summarize, we propose a unified/single utility structure for the three consumer decisions of store choice, category purchase incidence and SKU choice. In addition to the usually studied marketing mix variables, we also study how retail assortment affects the consumer choice process using two measures: a) assortment breadth (number of SKUs in category) and b) assortment depth (number of SKUs of a brand). We account for consumer heterogeneity and correct for price and assortment endogeneity. On the supply side, we estimate optimal pricing rules for retailers, taking into account consumer demand and assortment varying costs. The calibrated demand and supply models are used to simulate changes in equilibrium retail profits resulting from assortment reductions and targeted coupon programs.

3. Model

Using household level transaction data across multiple stores belonging to different chains, we propose an econometric model of demand and supply to address the implication of retail competition on retailer category pricing.

3.1 Demand Model

We model our demand function as a nested logit with SKU choice at the lowest level, then category purchase incidence, followed by store choice at the highest level. Figure 1.1 illustrates the consumer decision tree. We refer readers to Ben-Akiva and Lerman (1985) for a more detailed exposition of this demand specification.

Households are denoted by the subscript *i* (i=1,2,…,N), SKU by j (j=1,2,…,J), category purchase incidence by c (buy or no buy), stores by s, and shopping trip by t. For a three-dimensional choice set (store, incidence, SKU), the utility from alternative j for household i in store s at time t is given by

$$U_{ijcst} = V_{ijcst} + V_{icst} + V_{ist} + \varepsilon_{ist} + \varepsilon_{icst} + \varepsilon_{ijcst} \tag{1}$$

where V_{ijcst} , V_{icst} and V_{ist} are the deterministic components and ε 's are the stochastic components of consumer utility. Assuming that the ε 's are Gumbel distributed leads to a nested logit demand model. Each ε in the utility specification in equation (1) has a scale/dissimilarity/log-sum parameter associated with it. These are denoted by μ^{b} , μ^{inc} and μ^{s} for SKU, category purchase incidence and store choice levels respectively. For identification, we normalize one of the scale parameters, $\mu^{b} = 1$.

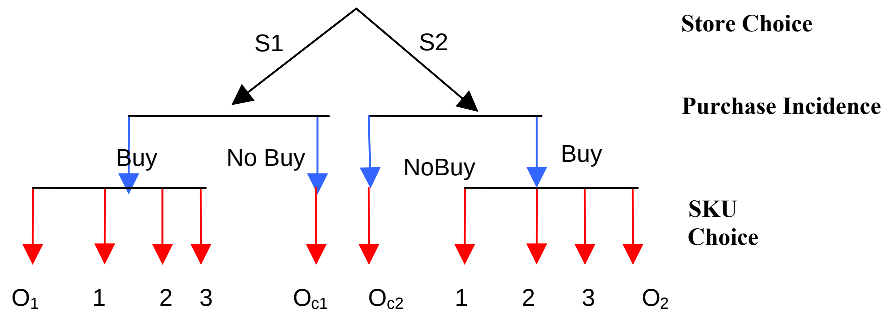


FIGURE 1.1: Consumer decision tree

3.1.1 Model For SKU Choice – Conditional on Store Choice and Category Purchase Incidence

The probability that household i purchases SKU j during shopping trip t in store s is denoted as P_{ijcst} . The vector of covariates includes SKU constant, price, SKU loyalty, feature, display and assortment depth (number of SKUs of focal brand)[3]. The assortment depth measure is used to capture the effect of brand salience on retailers' shelf on consumer utility and, hence, choice. In particular, does the presence of many SKUs of same brand affect consumer utility of a particular SKU?[4] These covariates

[3] The implicit assumption thoughout the modeling approach is that of rational expectations. We make the rational expectations assumption largely for methodological simplicity. The Bell and Lattin (1998) study of consumer demand relaxes the rational expectations assumption by using information from previous consumer shopping trips to inform consumer expectations of retailer activities in future store visits. Relaxing the rational expectations assumption is non- trivial in an equilibrium based model since this would warrant that retailers account for inter-temporal dependencies in their actions, i.e a dynamic model. Proposing a dynamic structural model of demand and supply while accounting for complexities of our model is beyond the scope of this study. However, it is a potentially interesting area for future research.

[4] There are several ways of increasing brand salience on retail shelf. For example, a retailer can a) stock multiple SKUs of a brand, b) use multiple facings of SKUs, or c) use many facings of some SKUs, etc. In the absence of data on facings, we are limited to capturing brand salience through a) alone. The author thanks Ram Rao and B.P.S. Murthi for bringing this model limitation to our attention.

are denoted by X_{jcst}. The SKU constant captures the effect of time invariant SKU fixed effects.

To account for potential non-linear brand specific assortment effects on consumer utility (Draganska and Jain, 2001), we include a linear-quadratic specification of assortment depth (number of SKUs belonging to the same brand as SKU *j*).

The vector of population mean covariate effects is denoted by β . All covariate effects are allowed to be household-specific and the household i specific deviation of covariate effects is denoted by $\Delta\beta_i$.

Hence, the effect of covariates for household *i* is given by $\beta + \Delta\beta_i$. Similarly, the mean responsiveness to price across households is α and the household i specific deviation for the responsiveness to price is $\Delta\alpha_i$. We assume that consumer response to marketing mix variables is store and time invariant. In this paper, we use random coefficients specification to account for unobserved consumer heterogeneity. In addition to X_{jcst}, there could be factors that are SKU-store-time specific that are invariant across households and influence household choices. These unobserved attributes might include factors like number of shelf facings of *j*, location on shelf, in-store feature, etc. These factors denoted by ξ_{jcst} can be correlated with price for that alternative. Failure to account for such correlation results in a biased estimate of the mean price response coefficient (Berry et al., 1995; Villas-Boas and Winer, 1999). Conditional on category purchase incidence *c* and store choice *s* at time *t*, making the logit distributional assumption on ε_{ijcst} , the conditional choice probability that household *i* chooses SKU *j* at time *t* is given by

$$P_{ij|cst} = \frac{\exp((\alpha+\Delta\alpha_i)p_{ijst} + X_{jst}(\beta+\Delta\beta_i)+\xi_{jcst})}{\sum_{k=1,k\in B_{cst}}^{J} \exp((\alpha+\Delta\alpha_i)p_{ikst} + X_{kst}(\beta+\Delta\beta_i)+\xi_{kcst})} \tag{2}$$

where B_{cst} is a set of focal SKUs in store s during shopping trip t. Without losing generality and for the purpose of econometric identification, utility from one/some of the SKUs in the analysis can be set to zero. This one/composite outside option (the J+1th SKU) is viewed as the "outside good" at the SKU level. Therefore the recovered parameters, in reality, are values relative to parameters of the outside good.

3.1.2 Model of Category Purchase Incidence Conditional on Store Choice

While equation (2) represents the conditional choice probability of one of the j=1,…J+1 SKUs, consumers might choose to not purchase in the category. This is the no-purchase option and is analogous to the outside good for category incidence. Hence a consumer decides to buy into a focal category if and only if the utility from buying into that focal category is greater than the consumer utility from buying into other categories. Setting the deterministic part of the utility $V_{i,nobuy,st}$ from no-purchase option (no purchase of 1..J+1 alternatives conditional on store choice) to be zero results in the following expression for category purchase incidence (buying into category)

$$P_{i,buy,st} = \frac{\exp\{(V_{i,buy,s,t} + V'_{i,buy,st})*\mu^{inc}\}}{1+\exp\{(V_{i,buy,s,t} + V'_{i,buy,st})*\mu^{inc}\}}$$

where
$$V'_{i,buy,s,t} = \frac{1}{\mu^b}\ln\left(\sum_{j\in B_{st}}\exp(V_{jcst}*\mu^b)\right)$$

and
$$V_{i,buy,s,t} = \upsilon_c + \upsilon_{ic} + \varsigma\times(q_{i,t-1} - R_i*\Delta_{i;t,t-1}) + \varsigma_i(q_{i,t-1} - R_i*\Delta_{i;t,t-1}) \tag{3}$$

μ^{inc} and μ^{b} are the scale parameters for category purchase incidence and SKU choice decision ε's and $V_{i,buy,s,t}$ is the indirect utility from purchase in focal category independent of $V'_{i,buy,st}$. In order to account for household consumption and inventory levels, we calculate the household inventory recursively for each shopping trip.[5] A similar approach has been used in Bucklin and Lattin (1991) and Gupta (1988) and Chintagunta (1993). We assume a constant consumption rate computed in the initialization sample. Let R_i denote the consumption rate (units/day, i.e. tissue rolls/day) for household i. Hence if $\Delta_{i;t,t-1}$ is the elapsed time (in days) since last purchase in category, then $R_i * \Delta_{i;t,t-1}$ is the total number of units consumed since last purchase. If $q_{i,t-1}$ denotes the number of units (rolls of tissue) purchased in the previous trip,[6] then the expression for $V_{i,buy,s,t}$ in equation (3) represents the indirect utility for household i from the focal category via a) the household time invariant intrinsic preference for the focal category and b) available household inventory during shopping trip t.

The 1 in the denominator of equation (3) is the result of setting the deterministic part of the outside good (no purchase option) to zero.

3.1.3 Store Choice Model

Bell and Lattin (1998) and Bell et al. (1998) conjecture a relationship between store choice and store-expenditure. To account for this relationship, we use expenditure on

[5] I thank Ambar Rao and Seethu Seetharaman for identifying the need to control for inventory even within a single SKU and Sachin Gupta for the appropriate model specification.

[6] While our model accounts for effects of multi-pack SKUs such as a multiple-roll pack of tissues, multi-pack beer SKUs or multi-pack carbonated drinks, we do not build an explicit model of quantity purchased as in Chintagunta (1993) and Chiang (1992). Hence our model is more appropriate for categories where consumers rarely stockpile SKUs and where SKUs might differ in size. This is the case with our focal category, toilet tissues, as explained later in the data and estimation sections.

current trip interacted with store specific dummy as a covariate in the consumers' store choice model. To capture the role of price image of the store on consumers' store choice probability, we add the average price of featured SKUs in the focal category, as another explanatory variable in the store choice model. A linear-quadratic specification of assortment breadth (total number of SKUs in category) captures potential non-linear category specific assortment effects on consumer utility. These factors are denoted by Z_{st}.

The store choice model is given by

$$P_{ist} = \frac{\exp(Z_{st}(\gamma + \Delta\gamma_i) + V'_{ist})}{\sum_{g=1}^{S} \exp(Z_{gt}(\gamma + \Delta\gamma_i) + V'_{igt})} \tag{4}$$

where
$$V'_{ist} = \frac{1}{\mu^s} \ln\left(\sum_{d \in E_{st}} \exp(V_{idst} * \mu^s)\right) \tag{5}$$

E_{st} is the set of incidence decisions [incidence (buy) or no-incidence (no-buy)] conditional on store choice s, and S is the total number of stores.

The nested demand model is therefore given by

$$P_{ijcst} = P_{ij|cst} * P_{ic|st} * P_{ist} \tag{6}$$

which implies

$$P_{ij,buy,st} = \frac{\exp((\alpha + \Delta\alpha_i)p_{ijst} + X_{jst}(\beta + \Delta\beta_i) + \xi_{jcst})}{\sum_{k=1, k \in B_{cst}}^{J} \exp((\alpha + \Delta\alpha_i)p_{ikst} + X_{kst}(\beta + \Delta\beta_i) + \xi_{kcst})} * \frac{\exp\{(V_{i,buy,s,t} + V'_{i,buy,s,t}) * \mu^{inc}\}}{1 + \exp\{(V_{i,buy,s,t} + V'_{i,buy,s,t}) * \mu^{inc}\}} * \frac{\exp(Z_{st}(\gamma + \Delta\gamma_i) + V'_{ist})}{\sum_{g=1}^{S} \exp(Z_{gt}(\gamma + \Delta\gamma_i) + V'_{igt})} \tag{7}$$

To capture unobserved consumer heterogeneity we assume that the individual response parameters $\Theta_i = [\alpha_i \ \beta_i \ \gamma_i]'$ come from a multivariate normal distribution

$$N\left(\begin{matrix}\bar{\alpha}\\ \bar{\beta}\\ \bar{\gamma}\end{matrix}, \Omega\right) \text{ such that } \begin{bmatrix}\alpha_i\\ \beta_i\\ \gamma_i\end{bmatrix} = \begin{bmatrix}\bar{\alpha}\\ \bar{\beta}\\ \bar{\gamma}\end{bmatrix} + \Sigma\vartheta_h, \vartheta_h \sim P^*_\vartheta(\vartheta)$$

where Σ is the lower triangular Cholesky factor of Ω and $P^*_\vartheta(\vartheta)$ is a multivariate normal distribution with zero mean.

Gathering terms that vary across households and those that do not, equation (7) can be written as follows

$$P_{ijcst} = \frac{\exp(\delta_{jst} + \omega_{ijst})}{\sum_{k=1,k\in B_{cst}}^{J} \exp(\delta_{kst} + \omega_{ikst})} * \frac{\exp(V_{icst} + V'_{icst})}{\sum_{m=buy}^{nobuy} \exp(V_{imst} + V'_{imst})} * \frac{\exp(\sigma_{st} + \kappa_{ist})}{\sum_{g=1}^{S} \exp(\sigma_{gt} + \kappa_{igt})} \qquad (8)$$

where $\delta_{jst} = \alpha p_{jst} + X_{jst}\beta' + \xi_{jcst}$ $\quad \omega_{ijst} = (p_{ijst}, X_{jst})'\Sigma\eta_i$ $\quad \sigma_{st} = Z_{st}\gamma + V'_{st}$

$$\kappa_{ist} = (Z_{st}, V'_{ist})\Sigma\eta_i \qquad (9)$$

Here δ_{jst} and σ_{st} are the mean utilities across households for SKU j and store s in week t respectively. Notice from equation (9) that the term δ_{jst} contains the mean effects of marketing activities as well as the unobserved attribute term ξ_{jcst}, a feature we exploit in our estimation procedure to correct for endogeneity.

3.2 Supply Model

Assuming that retailers set prices to maximize category profits, the category profit for store *s* in week *t* is given by

$$\Pi_{st} = \sum_{j\in B_{st}} (p_{jst} - mc_{jst}) S_{jst} M_t \qquad (10)$$

where S_{jst} is the share of SKU j in store s in week t and M_t is the market size in week t. mc_{jst} is the marginal cost of j in store s at time t. S_{jst} can be viewed as the fraction of trips to store s in week t that have led to purchase of j[7].

3.2.1 Modeling Cost

The Besanko, Gupta and Jain (1998) and the Sudhir (2001) studies use data from a single retail account, and have access to wholesale price net of trade promotions for their focal categories. This enables these studies to account for wholesale price levels in their retail category pricing analysis. Observed retail prices and manufacturer wholesale prices facilitate recovery of retailer markups from the estimation of the retailer pricing rules. In this regard, data used for the current study pose some limitations. While the data used in this study overcome the single retail account limitation of data used in previous studies, they do not contain manufacturer deals to individual retailers/retail accounts. Since manufacturer deals to retailers and retail competition affect retailer category pricing decisions (Lal and Villas-Boas, 1998; Pesendorfer, 2001), a key modeling challenge for us is to account for manufacturer-retailer dealings/retailer costs unobserved in our data.

The literature recognizes several factors that influence retailers' cost structure, such as wholesale prices (Besanko, Gupta and Jain, 1998; Sudhir,2001); manufacturer induced trade-promotions (Dreze and Bell 2000; Lariviere and Padmanabhan 1997); and lump-sum side payments (Blattberg and Neslin, 1990; Chintagunta, 2002). While the Robinson-Patman Act prevents manufacturers from discriminating on wholesale prices among competing retailers within a trading region, manufactures can employ

---

[7] Since the focus of this paper is very different from that of Chintagunta (2002) and Sudhir (2001), we do not test for strategic departures from the standard category profit maximization assumption. This is not a modeling limitation, however, and can be easily accommodated in our estimation.

instruments like the ones listed above to discriminate among competing retailers. This means retailers can potentially face different costs (Shugan and Desiraju, 2001).

Consequently, an empirical methodology would be needed that can estimate these retailer varying cost factors from the data -- and then explain their role on the retailers' pricing behavior when coupled with retail competition and demand side factors.

We achieve this by parameterizing the marginal costs of retailers to include retailer-specific costs due to manufacturer deals and retail assortments. By allowing retailer-specific manufacturer deals, we try to account for manufacturer-retailer dealings W_{jst} -- net of wholesale prices, side-payments, quantity discounting and trade-promotions activities unobserved by the econometrician.

Like the demand model that is developed at the SKU-store-week level, the cost model for retailer is parameterized at the SKU-store-week level as follows

$$mc_{jst} = W_{jst}\tau_s + Asst_{jst} * \lambda_{1s} + Asst_{jst}^2 * \lambda_{2s} + \varsigma_{jst} \tag{11}$$

where W_{jst} is the manufacturer deal price of SKU j to store s at time t and ς_{jst} is a zero mean stochastic cost shock. Note that not only does our specification allow for costs to vary across retailers, but it also allows for retailers to react differently to these cost factors.

While deGroote (1994), Kekre and Srinivasan (1990) and Draganska and Jain (2001) focus on costs incurred by manufacturers as a result of adding variants to their product lines, van Ryzin and Mahajan (1999) and Krishnan et al. (2002) focus on retailer level costs of assortment. While setup costs might be small for the retailer, constrained shelf space forces a retailer to make tradeoffs in assortments in order to minimize costs due to stock-outs and overstocking. Increasing assortment may decrease demand for each SKU in the product category and increase variability of demand and, therefore, inventorying costs.

Faced with limited shelf space, retailers often charge premium slotting fees as an incentive to stock more variants of the manufacturers' product line. The amount can be as high as $10 per facing per week (AC Nielsen, 2000 survey). These arrangements can be moderated by retailer-manufacturer negotiations, retailer-specific shelf space and inventory/storage restrictions.

Substituting (11) in (10) and taking partial derivate of (10) with respect to p_{jst}, yields the first order optimization rule for price p_{jst} given by

$$\frac{\partial \Pi_{st}}{\partial p_{jst}} = p_{jst} M_t \frac{\partial S_{jst}}{\partial p_{jst}} + M_t S_{jst} + \sum_{k \in B_{st}, k \neq j} (p_{kst} - mc_{kst}) \frac{\partial S_{kst}}{\partial p_{jst}} M_t$$

$$p^*_{jst} = \frac{S_{jst} + \sum_{k \in B_{st}, k \neq j} (p_{kst} - mc_{kst}) \frac{\partial S_{kst}}{\partial p_{jst}} M_t}{-\frac{\partial S_{jst}}{\partial p_{jst}}} \tag{12}$$

The system of equations given by equation (12) forms the estimation equations for pricing rules for category profit maximizing retailers with retail competition. It's worth pointing out that

$$S_{jst} = \sum_{i \in \Delta_t} \sum_{d \in D_{it}} P^d_{ijcst} * P^d_{icst} * P^d_{st}$$

where Δ_t is the set of all households making shopping trips in week t, and D_{it} indexes the number of trips made by household i in week t[8].

4. Data And Estimation

4.1 Data

We estimate our model using the IRI database that includes purchase histories of 520 households over two years (June 1991-June 1993) in five grocery stores. The stores include two Every Day Low Price (EDLP) format stores and three promotion or HILO stores. Two of the HILO stores belong to the same retail chain. There are 24 product categories in the data. However we selected tissues as the focal category in this study for the following reasons: a) large number of repeat purchases by households b) significant price and assortment variation across stores and c) we do not observe households buying multiple SKUs or multiple quantities of same SKU in the data[9], which makes the results not very sensitive to our discrete quantity/choice assumption.

Table 1.1 reflects the descriptive statistics for the sample, pooling observations across the five stores. Table 1.2 provides detailed store level statistics. It suggests that while there is cross-sectional variation in price and assortment across stores, there isn't much longitudinal variation in category assortment breadth within a store.

[8] Our specification assumes that the sample is representative of the market, and firms set prices based on the behavior of the panelists. In future work we will try to relax this assumption by combining micro (panel) data and macro (store SKU level) data.

[9] Twenty-eight of the 520 households buy multiple SKUs during a shopping trip.

While there is variation in assortment size across stores, a closer examination of the data suggests a) each store maintains a consistent number of SKUs in the category and b) assortment size changes (if any) do not happen on a week-by-week basis. Therefore we treat assortment size to be an exogenous decision[10].

TABLE 1.1 – Descriptive Statistics For Full Sample (All Shopping Trips)

Variable	Mean	Std. Dev	Minimum	Maximum
SKU's purchased	1.455162	0.898774	1	24
Price (per unit)	0.957153	0.220833	0.48	1.63
Feature	1.438581	1.552719	0	4
Display	0.962947	1.485691	0	7
Trip Expenditure	25.46179	30.10319	0	378.4
Assortment Breadth	16.51	2.1324	11	22

[10] Maintaining consistent assortments can be a strategic choice on the part of retailers. Modeling this choice is beyond the scope and focus of the current study. We do, however, intend to address this issue in future research.

TABLE 1.2 (a) – Descriptive Statistics By Store (Only Purchase Observations)

EDLP 1

Variable	N	Mean	Std Dev	Minimum	Maximum
SKU's Purchased	1091	1.669111	1.240579	1	24
Coupon_Val	1091	5.202567	15.86307	0	128
Price	1091	0.867021	0.154431	0.48	1.28
Feature	1091	1.048579	1.414352	0	4
Display	1091	0.425298	0.739862	0	4
Assortment Breadth	104	18.125	1.580755	13	21

EDLP 2

Variable	N	Mean	Std Dev	Minimum	Maximum
SKU's Purchased	1603	1.569557	0.862231	1	7
Coupon_Val	1603	3.28821	14.14657	0	192
Price	1603	0.922633	0.131381	0.58	1.28
Feature	1603	1.144105	1.433876	0	3
Display	1603	1.414223	2.028658	0	7
Assortment Breadth	104	14.66346	1.604669	11	19

HILO 1

Variable	N	Mean	Std Dev	Minimum	Maximum
SKU's Purchased	2432	1.332237	0.77697	1	13
Coupon_Val	2432	5.956826	15.59518	0	189
Price	2432	0.938409	0.190867	0.49	1.63
Feature	2432	1.962582	1.630589	0	4
Display	2432	0.844984	1.025499	0	6
Assortment Breadth	104	15.98077	1.190421	14	18

TABLE 1.2 (b)– Descriptive Statistics By Store (Only Purchase Observations) (continued)

HILO 2

Variable	N	Mean	Std Dev	Minimum	Maximum
SKU's Purchased	591	1.263959	0.553605	1	4
Coupon_Val	591	2.592217	13.58942	0	149
Price	591	1.109492	0.316599	0.49	1.63
Feature	591	1.128596	1.312409	0	4
Display	591	1.441624	1.926504	0	5
Assortment Breadth	104	17.10577	1.253487	14	20

HILO 3

Variable	N	Mean	Std Dev	Minimum	Maximum
SKU's Purchased	684	1.372807	0.745837	1	7
Coupon_Val	684	3.669591	12.99889	0	113
Price	684	1.143801	0.311614	0.49	1.63
Feature	684	0.975146	1.308032	0	4
Display	684	0.73538	1.434313	0	4
Assortment Breadth	104	15.98077	1.190421	14	18

4.2 Estimation

The focus of this study is to model households' category purchase decisions among five competing retailers. However in the data, choices at the individual level are fairly sparse. Therefore, we need an estimation procedure that can estimate the proposed demand model at the individual level, even with limited household level data. The hierarchical Bayes estimation framework is an ideal fit for such a situation. The hierarchical Bayes, (henceforth HB) estimation framework pools information across individuals (Gelfand and Smith 1990; Rossi, McCulloch, and Allenby, 1996). Thus the HB procedure allows sharing of information across subjects, and the inference of household specific parameters in a single, unified framework. This estimation procedure, therefore, allows us to get a more detailed understanding of the effects of retailers' decisions on household choices. In this approach, household specific parameters are drawn from a normal distribution as explained in the model development section. A similar approach has been employed by Chintagunta et al. (2003), although they use a simulated maximum likelihood estimation procedure. Although the Bayes estimates and the simulated maximum likelihood estimates are asymptotically equivalent (Huber and Train, 2003), they might yield different results for small samples.

The first stage of the estimation procedure results in a full set of household-invariant weekly fixed effects δ_{jst}, which capture the mean utility from each SKU-store-week combination. One should note that the fixed effects subsume in them the mean effects of the marketing mix variables and the unobserved component ξ. Rewriting (8) we have

$$P_{ijcst} = \frac{\exp(\delta_{jst} + \omega_{ijst})}{\sum_{k=1,k\in B_{cst}}^{J} \exp(\delta_{kst} + \omega_{ikst})} * \frac{\exp(V'_{icst})}{\sum_{m=buy}^{nobuy} \exp(V'_{imst})} * \frac{\exp(\sigma_{st} + \kappa_{ist})}{\sum_{g=1}^{S} \exp(\sigma_{gt} + \kappa_{igt})}$$

We will make the following distributional assumptions in order to be able to estimate the model for an arbitrary household. The random effects parameters Θ_i, are distributed **N$_r$**(Θ, Ξ), i.e., the r-dimensional multivariate normal distribution with mean vector Θ and covariance matrix Ξ. Using Bayes rule (e.g., Gelman et al., 1995), we obtain information about the household specific parameters Θ_i, and the common parameters of the mixing distribution Θ, Ξ, by reformulating the likelihood function as a hierarchical Bayes model. The likelihood function is

$$L(\Theta_i, \Theta, \Xi) \equiv \text{Prob}(data \mid \Theta_i, \Theta, \Xi) = \prod_{i=1}^{N} L_i(\Theta_i) N(\Theta_i \mid \Theta, \Xi)$$

where $L_i(\Theta_i)$ is the likelihood of household i's data conditional on Θ_i. From Bayes rule we know that the joint posterior distribution of the parameters is proportional to the likelihood times the prior distribution, that is

$$P(\Theta_i, \Theta, \Xi \mid data) \propto \prod_{i=1}^{N} L_i(\Theta_i) N(\Theta_i \mid \Theta, \Xi) g(\Theta, \Xi)$$

In this formulation the mixing distribution is part of the prior distribution, where $g(\Theta, \Xi)$ is a prior distribution placed on Θ and Ξ in order to make sure that the joint posterior distribution will be defined. For convenience we use natural conjugate priors in which the prior on Θ is normal and the prior on Ξ is the inverted Wishart distribution. Draws from this joint posterior distribution are obtained through Gibbs sampling. That is, a sequence of conditional draws is obtained where each parameter is drawn conditional on a draw from the other parameters. See Casella and George (1992) and Smith and Gelfand (1992) for more information on the Gibbs sampler. In Gibbs sampling, draws of Θ are obtained from its posterior conditional on draws of Θ_i and Ξ $\forall i$. Similarly, draws of Ξ are obtained from its posterior conditional on Θ and Θ_i for $\forall i$. The Gibbs sampling provides a set of draws of Θ_i from its posterior distribution, and it is the mean of these draws that is the desired parameter estimate. Interested readers may refer to Allenby and Lenk (1994), Allenby and Rossi

(1999), Chib et al. (1998), Huber and Train (2000), and Gelman et al. (1995) for a more detailed explanation of the computation procedure.

At this stage of the estimation process we obtain the SKU-store-week specific fixed effects, variance of the household varying (heterogeneity) parameters and the variance-covariance matrix for these. Note that we don't need to rely on any inversion techniques (e.g. Goolsbee and Petrin, 2001) or contraction mapping procedure like Berry, Levinsohn and Pakes (1995) to recover the fixed effects. Since the asymptotic properties of the estimator are well understood, and the simulated maximum likelihood estimates of the demand model are recovered, the proposed estimation procedure is more efficient than the ones that rely on contraction mapping (Chintagunta et al. 2002).

Next we regress the estimated SKU-store-week fixed effects δ_{jst} on the respective marketing mix variables. Note that the unobserved component ξ subsumed in the fixed effect now acts as the error term for second stage regression. ξ can be correlated with one or many of the regressors, hence the OLS estimator is inconsistent. We therefore employ the 2SLS estimator to recover the mean response parameters while instrumenting for price and assortment breadth.

$$\hat{\delta}_{jst} = \alpha p_{jst} + X_{jst}\beta' + \xi_{jcst}$$

Since we do not have wholesale prices in our data, we rely on manufacturer level production factor price indices[11] along with two-week lags of retail prices [12] as instruments for price, and two-week lags assortment depth as instruments for

[11] Weekly price indices for paper pulp, resins and plastic were obtained from the Chicago Mercantile Stock Exchange and Bureau of Labor Statistics.

[12] We checked for robustness of our specification by increasing number of lags. The results do not change substantively.

assortment depth (brand level). Since manufacturers differ in their production efficiencies and can offer different prices per SKU to retailers, we interact the input factor cost shifters with the respective SKU and store dummies.

If V is the matrix of instruments and E a matrix containing X, Z and p_{jst}, the population mean parameters $[\alpha\ \beta]$ are given by

$$[\alpha\ \beta]=[E'\Omega_V E']^{-1}E'\Omega_V \hat{\delta}_{jst}$$

where

$$\Omega_V = V(V'V)^{-1}V'$$

The standard errors are given by

$$Var[\alpha\ \beta]=\mathrm{s}^2[E'\Omega_V E]^{-1}$$

where

$$\mathrm{s}^2 = \frac{(\hat{\delta}_{jst}-\alpha p_{jst}+X_{jst}\beta)'(\hat{\delta}_{jst}-\alpha p_{jst}+X_{jst}\beta)}{T-K}$$

and K is dimension of β +1 (to account for α).

Treating the demand parameters as given, we estimate a system of first order optimization rules for price for the competing stores. Here we regress (12) to recover the marginal cost parameters τ_s, λ_{1s} and λ_{2s}.

5. Results

A homogenous nested logit based demand model is used as the base model[13]. Inference of the full model, i.e. mixed nested logit, is made using hierarchical Bayes

[13] A demand model wherein the three consumer choice decisions are modeled as being independent, i.e. joint demand model is the product of three independent logits, was also estimated. Interested readers can contact the authors for these results.

estimation procedure after discarding the first 5000 draws in the burn-in period (Gelman and Rubin, 1992). In Table 1.3, we present the estimates for the two demand models a) the Base Model (homogenous nested logit) and b) Full Model (mixed nested logit).

The Full model that accounts for consumer heterogeneity outperforms the Base model (AIC Full Model<AIC Base Model and BIC Full Model< BIC Base Model). As explained in the model specification section, we observe that the SKU intercepts are smaller in the Full Model than Base Model. This is because some of the variance due to unobserved taste heterogeneity was being incorrectly attributed to the SKU intercepts in the Base Model. Note that the mean price response coefficient is underestimated when we do not account for unobserved consumer heterogeneity. The average price of the featured items in the category, i.e. the price image variable, has a statistically significant effect on the store choice decision. Like the Bell et al. (1998) study, we find a direct effect of consumer trip expenditure on consumer store choice decisions.

EDLP stores on average have larger store intercepts than HILO stores. Accounting for both the signs and magnitudes of the estimates for a) store intercepts and b) trip expenditure, suggests that consumers who spend more (large basket shoppers) -- all else being -- equal prefer EDLP stores to HILO stores, a result consistent with Bell and Lattin (1998). The average price elasticities for SKU choice and store choice are 1.83 and 1.28 respectively. This means a 1% reduction in retailer's price of an SKU results in a 1.83% increase in the choice probability of that SKU, while a 1% reduction in the retailer's average price of featured items results in 1.28% increase in choice probability of that SKU. There is also significant heterogeneity in the response to price.

The demand model results indicate that consumers are making tradeoffs in price and assortment. The corresponding heterogeneity parameters reflect that there is significant heterogeneity in preference for assortment depth and breadth. Since we have two measures of assortment, we can compute consumer willingness to pay for assortment breadth and depth. We find that consumers are willing to pay 1.09 cents per SKU for a 1% increase in assortment depth and .24 cents per SKU for a 1% increase in assortment breadth. Thus, in our data consumers have stronger preference for assortment depth than assortment breadth, as demonstrated in their willingness to pay for assortments.

A summary of the signs and significance of the individual-specific effects is given in Table 1.4. The second column represents the number of households whose preference parameter for the corresponding explanatory variable in the first column is less than zero. The third column is the corresponding number of households whose preference parameter is significantly less than 0 at the 5% level ($p^{-}<.05$) and the fourth column is the number of households whose corresponding preference parameter is significantly greater than 0 at the 5% level ($p^{+}<.05$). The results indicate that most consumers are estimated to derive negative utility from higher prices and shopping trip expenditures, and positive utility from assortment depth and breadth. This provides face validity to the estimated individual-level posterior demand estimates. We also find diminishing marginal utility in both assortment depth and breadth.

Note from Table 1.3, the log sum/dissimilarity parameters for category incidence and store choice decisions are significant and their magnitudes are consistent with utility maximization[14] (μ_s = .05, μ_c =0.11). The statistical significance of these parameters supports dependence between the three consumer decisions of consumer store choice, category purchase incidence and SKU choice.

The supply side estimates are presented in Table 1.5. Consistent with the theoretical predictions, we find that assortment affects retailer costs. Since our marginal cost specification is store specific, we compute the cost elasticities due to assortments across EDLP and HILO stores. The marginal cost elasticity due to assortment averaged across all five stores is 1.2. This means that all else being equal, if a retailer increases its assortment breadth by 1% , its marginal cost increases by 1.2%. The ratio of marginal elasticities of EDLP and HILO stores is .84. This suggests that EDLP stores are more efficient in increasing assortment breadth than HILO stores.

As explained in the estimation section, the analytics developed in this study can be used by retailers to get a more detailed understanding of effects of their marketing mix decisions on household choices while accounting for response from competitors.

[14] To be consistent with utility maximization, the log-sum parameters must be in the range (0,1].

TABLE 1.3– Demand Model Results

		Homogenous Nested Logit Demand Model	Hierarchical Bayes Mixed Nested Logit Demand Model	
			Mean	Heterogeneity
	Parameter	Estimate	Estimate	Estimate
SKU CHOICE MODEL	SKU1	-3.09	-1.90	5.61
	SKU2	-2.26	-0.92	4.42
	SKU3	-2.65	-0.73	2.72
	SKU4	-2.44	-0.89	6.91
	SKU5	-2.67	-0.99	5.42
	SKU6	-2.49	-0.90	1.93
	SKU7	-2.07	-0.80	5.73
	SKU8	-2.42	-0.89	1.25
	SKU9	-2.04	-0.79	8.90
	SKU10	-2.25	-0.77	8.95
	Price	-1.31	-2.08	2.26
	Assort. Depth	0.20	0.90	3.72
	Assort. Depth^2	-0.09	-0.08	0.12
CATEGORY INCIDENCE	$1/\mu_c$	9.35	8.73	
STORE CHOICE	EDLP1	6.03	7.01	3.98
	EDLP2	1.33	1.39	7.53
	HILO1	-0.61	-1.75	2.28
	HILO2	-0.53	-1.15	8.01
	Average Price	-0.27	-2.31	4.33
	Assort. Breadth	0.14	0.30	11.15
	Assort. Breadth^2	-0.03**	-0.09**	0.77
	Trip Spend	-0.78	-0.64	12.96
	$1/\mu_s$	26.82	18.35	
Number of Observations	89056			
Number of Cases	2118710			
Log Likelihood	-55052.00		-31023.12	
AIC	10162.00		8096.10	
BIC	11410.17		8167.69	

*** implies statistically not significant**

TABLE 1.4 – Individual Main Effects

Covariates	# ($\beta < 0$)	# ($\beta < 0$) (p-<.05)	# ($\beta > 0$) (p+<.05)
Price	485	412	21
Assortment Depth	18	9	489
Assortment Depth^2	501	467	18
Feature	39	13	457
Display	128	104	156
Average Price	518	491	15
Assortment Breadth	264	243	194
Assortment Breadth^2	412	42	56
Trip Spend	503	444	17

Using the proposed demand and supply models, retailers can identify a) which households are store loyal and which households are more prone to store switching b) which households are price/assortment sensitive and c) which households are more sensitive to assortment depth or assortment breadth. Answers to these questions provide valuable insights for retailer category pricing.

We use the estimated demand and supply models to conduct two policy experiments. We examine the equilibrium implications of a) assortment reduction and b) price promotions via targeted/customized coupons on retailer profits.

TABLE 1.5 – Supply Side Estimates

	Parameter	Estimate
Store Intercept	EDLP1	1.36
	EDLP2	2.55
	HILO1	3.00
	HILO2	4.11
	HILO3	3.19
Assortment Breadth	EDLP1	7.25
	EDLP2	5.31
	HILO1	12.13
	HILO2	7.43
	HILO3	7.52
Assortment Breadth^2	EDLP1	0.53**
	EDLP2	0.23**
	HILO1	0.49
	HILO2	0.42**
	HILO3	0.27**
Plastic	EDLP1	0.08
	EDLP2	1.13
	HILO1	1.67
	HILO2	1.69
	HILO3	2.66
Paper	EDLP1	3.24
	EDLP2	3.86
	HILO1	4.00
	HILO2	3.38
	HILO3	-4.26**
Resins	EDLP1	0.77
	EDLP2	0.47
	HILO1	1.08
	HILO2	1.05**
	HILO3	1.73

**** implies not statistically significant**

6. Policy Experiments

6.1. Assortment reduction

The question of assortment reduction has recently been receiving considerable attention. The previous studies differ both in terms of methodology and data used. In an experimental setting, Broniarczyk, Hoyer, and McAlister (1998) find consumers' assortment perceptions -- hence sales -- to be unchanged even after dramatic reduction in the number of SKUs in the category. This suggests that retailers can reduce their assortment without any significant change or decrease in sales.

In contrast to the previous finding, in a field study Dreze, Hoch, and Purk (1994) show that aggregate sales went up nearly 4% when 10% of the less popular SKUs were deleted, while dedicating greater shelf space to more popular items. Boatwright and Nunes' (2001) study of an online grocery retailer also finds a significant increase in category sales as a result of assortment reduction.

Borle et al. (2002) find significant reduction in consumer purchase frequency and purchase quantity as a result of assortment reductions. Fox et al. (2003) show consumers' spending levels to be sensitive to both retail assortment levels and varying across retail formats.

Hence there is conflicting evidence on the effects of category level assortment reduction at retail sales. While previous studies have tried to understand how assortment reduction affects retail sales, the proposed structural model allows us to understand how assortment reductions affect retail profits. Using the calibrated demand and supply models, we conduct two exercises to study the implications of assortment reduction on consumer choice and retailer profits. We thereby address the need identified by Fox et al. (2003) to understand the implications of assortment reduction on store patronage.

We simulate two exogenous assortment reduction scenarios.

a) Scenario 1: A single SKU manufacturer (manufacturer of the smallest share focal SKU) exits the market, i.e. a brand is removed from assortment of all retailers. In the face of competitive pressure, manufacturers often crop their product lines. Hence this policy experiment helps shed light on the implications of manufacturer decisions on retailer profits.

b) Scenario 2: A retail account manager might decide to reduce the retail shelf space for the focal category to accommodate expansion of other categories. Before making this decision, an account manager might be interested in studying how their decision affects their category profits. We simulate such a scenario by studying the equilibrium profit implications when the retail account manager of the HILO store managing two HILO stores in the data drops the SKU with the smallest share in its stores.

We compute household level choices and equilibrium prices after dropping the respective items in scenarios 1 and 2. Our computed demand results indicate significant decrease in category purchase incidence and store choice probabilities across both scenarios from numbers without assortment reduction.

In scenario 1 the category purchase incidence and store traffic reduction is larger for HILO stores than EDLP stores (2.87% vs. 1.003%). All retailers incur reduced profits from assortment reduction, with EDLP stores incurring smaller changes in profits than

HILO stores (.88% vs. 1.12%). Therefore we find evidence of asymmetric effects in assortment reduction across stores belonging to different price formats. In scenario 2 the stores that reduce their assortment incur reduction in category profits (-1.01%) while the other stores gain in equilibrium profits. The gains are asymmetric with the third HILO store gaining more than the two EDLP stores (3.04% vs. 2.11%).

Thus assortment reduction affects consumer decision of store choice, category incidence and SKU choice. Assortment reduction also affects retailers' category profit, and these effects are sensitive to retailer price format.

6.2. Targeted coupons

Coupons enable firms to price discriminate between price-elastic and price-inelastic consumers (Narasimhan, 1984), thereby increasing firm profits. For example, Rossi and Allenby (1996) demonstrate that manufacturer profits from targeted coupons are as much as 2.5 times the profits from blanket coupon programs. Another view in the literature is that coupons reduce consumers' switching costs, thereby increasing price competition (Shaffer and Zhang, 1995; Bester and Petrakis, 1996) and reducing equilibrium profits. However, all these papers have considered only the perspective of manufacturers. Our analysis provides empirical insights into the question of gains from targeted couponing by retailers.

We simulate a scenario wherein retailers offer targeted coupons. We assume that retailers offer targeted coupons for the smallest share SKU, with the intent of increasing sales/share of that SKU. The computational approach is similar to Rossi et al. (1996). While Rossi et al. (1996) conduct their analysis for manufacturers, we present an equilibrium solution accounting for retail competition. The objective is to calculate the optimal face value for household specific coupon for the lowest share SKU for each household-store-trip combination. For identification purposes, the analysis is conducted assuming that coupons are issued only to households having negative price preference parameter. The optimum face values are recovered by differencing the retail price (price offered to non-targeted consumers) from the optimal prices computed for each household-store-trip combination.

We find stores on average offer lower face value coupons to high store and SKU loyal households than low store or SKU loyal households (22 cents vs. 39 cents). Also EDLP stores on average offer smaller face value coupons than HILO stores (ratio is .48). Furthermore while EDLP stores offer smaller face value coupons, they incur reduction in profits due to targeting (-3.43%), while higher face value issuing HILO stores gain in profits (+4.97%) due to targeted coupon programs. This is in part because targeted coupons result in a) a smaller increase in sales for EDLP than HILO stores and b) a larger reduction in equilibrium prices on other focal SKUs in EDLP stores than HILO stores. This result offers some rationale as to why HILO stores price promote while EDLP stores do not.

7. Conclusion

Issues of retail competition have not received as much attention in the structural modeling literature. We address this gap in the literature by modeling competition between grocery retail stores in a single category. We do this by proposing a unified utility structure that nests the three consumer decisions of store choice, category purchase incidence and SKU choice. We estimate the demand model using household scanner panel data while accounting for consumer heterogeneity. In addition to the usually studied marketing-mix variables of price, feature and display, we also study the role of assortment breadth (number of SKUs in category) and assortment depth (number of SKUs of each brand) in the consumer choice process. We study category level retail competition by specifying a Bertrand-Nash pricing game and estimate the resulting equilibrium pricing equations to obtain marginal cost estimates.

We use the proposed structural model to address questions about retail competition such as: a) What tradeoffs do consumers make in price and assortments? b) How does assortment reduction affect retailer profits? c) What are the implications for retailer profits if retailers were to issue targeted retail coupons? d) Are these effects different for retailers belonging to different price formats?

To summarize, our empirical findings suggest price and assortment play a significant role in retail competition. We find that consumers do make tradeoffs in price and assortments, and are willing to pay more for greater assortment depth (more SKUs of a brand) than greater assortment breadth (more SKUs in category). Assortment also affects retailer costs. Assortment reduction and retailer issued targeted coupons affect equilibrium profits for retailers, and these effects vary by retailers' price format. We find greater price and assortment competition between stores that belong to the same price format than across price formats. We hope that our proposed model and empirical findings spawn ideas for future research in the area.

REFERENCES

Alba, Joseph W., Susan M. Broniarczyk, Terence A. Shimp, and Joel E. Urbany, (1994). “The Influence of Prior Beliefs, Frequency Cues, and Magnitude Cues on Consumers’ Perceptions of Comparative Price Data,” *Journal of Consumer Research*, 21, 2, 219–235.

Allenby, Greg M. and James L. Ginter, (1995). "Using Extremes to Design Products and Segment Markets," *Journal of Marketing Research*, 32, 392-403.

Allenby, G.M and P.E. Rossi, (1999), “Marketing Models of Consumer Heterogeneity,” *Journal of Econometrics*, 89, 57-78.

Arnold, Stephen J., Oum, Tae H. and Tigert, Douglas J., (1983). “Determining Attributes in Retail Patronage: Seasonal, Temporal, Regional and International Comparisons,” *Journal of Marketing Research* **20** May, pp. 149–157.

Baumol W. and Ide. W. (1956). "Variety in Retailing," *Management Science* (October), 93–101.

Bell, David, R. and Lattin, James, (1998). "Shopping Behavior and Consumer Preference for Store Price Format: Why `Large Basket’ Shoppers Prefer EDLP," *Marketing Science*, 17 (1), 66-88.

Bell, D. R. Teck-Hua Ho, and Christopher S. Tang, (1998). "Determining Where to Shop: Fixed and Variable Costs of Shipping," *Journal of Marketing Research*, 35 (August 1998), 352-369.

Ben-Akiva, Moshe and Steven R. Lerman (1985). *Discrete Analysis: Theory and Application to Travel Demand*, Cambridge, MA: The MIT Press.

Berry, S., J. Levinsohn, and A. Pakes, (1995). “Automobile Prices in Market Equilibrium,” *Econometrica*, 63, 841-890.

Berto Villas-Boas, S. (2002), “Vertical Contracts Between Manufacturers and

Retailers: An Empirical Analysis," University of California, Berkeley, *Working Paper*.

Besanko, D., S. Gupta and D. Jain, (1998). "Logit Demand Estimation Under Competitive Pricing Behavior: An Equilibrium Framework," *Management Science*.

Besanko, D., J.-P. Dubé and S. Gupta (2003). "Competitive Price Discrimination Strategies in a Vertical Channel using Aggregate Retail Data," *Management Science, forthcoming*.

Bester, H. and Petrakis, E., (1996). "Coupons and Oligopolistic Price Discrimination," *International Journal of Industrial Organization,* 14, (1996), 227-242.

Boatwright, Peter and Joseph C. Nunes (2001). "Reducing Assortment: An Attribute-Based Approach", *Journal of Marketing*, 65 (July), 50-63.

Boatwright, Peter, Robert McCulloch and Peter Rossi (1999). "Account-Level Modeling for Trade Promotion: An Application of a Constrained Parameter Hierarchical Model", *Journal of the American Statistical Association*, 94, 1063-1073

Borle, Sharad, Peter Boatwright, Joseph Kadane, Joe Nunes and Galit Shmueli, (2002), "Effect of Product Assortment Changes on Customer Retention", GSIA Carnegie Mellon University, *Working paper*.

Broniarczyk, Susan M., Wayne D. Hoyer and Leigh McAlister (1998), "Consumers' Perceptions of the Assortment Offered in a Grocery Category: The Impact of Item Reduction", *Journal of Marketing Research*, 35 (May), 166-176.

Bucklin, R., and Lattin, James (1992), "A Model of Product Category Competition Among Grocery Retailers," *Journal of Retailing*, 68, Fall, 271–293.

Chintagunta, P. (2002), "Investigating Category Profit Maximization at a Retail Chain." *Journal of Marketing Research*, 39, no. 2 (May): p. 141-154.

Chintagunta, Pradeep, Dubé Jean-Pierre and Goh, Khim Yon. (2002). "Investigating the effects of unmeasured brand characteristics in demand models for household panel data. Graduate School of Business, University of Chicago, *Working paper*.

Chintagunta, Pradeep, Dipak C. Jain and Naufel J. Vilcassim, (1991) "Investigating Heterogeneity in Brand Preferences in Logit Models for Panel Data", *Journal of Marketing Research*, 33 (Nov), 417-428.

Corstjens, Marcel and Doyle, Peter, 1981. A Model for Optimizing Retail Space Allocations. *Journal of Marketing*, 27 July, pp. 822–833.

Dickson, Peter and Alan Sawyer (1990), "The Price Knowledge and Search of Supermarket Shoppers," *Journal of Marketing*, 54, July, 42–53.

Dreze, Xavier, Hoch, Stephen J. and Purk, Mary E., 1994. Shelf Management and Space Elasticity. *Journal of Retailing,* 70 Fall, pp. 301–326.

Draganska, M. and D.C. Jain, (2001). "Product Line Length and Competitive Pricing: An Empirical Study," *working paper*, Northwestern University.

Heckman, James and Burton Singer, (1984). "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data," *Econometrica*. 52(2): 271-320.

Ho, Teck-Hua, Christopher S. Tang, and David R. Bell, (1998). "Rational Shopping Behavior and the Option Value of Variable Pricing," *Management Science*.

Hoch, Stephen J., Xavier Dreze, and Mary E. Purk, (1994). "EDLP, Hi-Lo, and Margin Arithmetic," *Journal of Marketing*, 58, 16–27.

deGroote, X., (1994). "Flexibility and marketing/manufacturing coordination", *International Journal of Production Economics*, Vol. 36, No. 2, 153-167.

Drèze, Xavier, Stephen J. Hoch and Mary E. Purk, (1994), "Shelf Management and Space Elasticity", *Journal of Retailing*, 70(4), 301-326.

Fox J. Edward, Alan L. Montgomery and Leonard M. Lodish, (2003). "Consumer Shopping and Spending Across Retail Formats," *Journal of Business*, forthcoming.

Gelfand A. E. and Smith, A. F. M., (1990). "Sampling-Based Approaches to Calculating Marginal Densities," *JASA* 85 (410): 398-409.

Gelman, J.B. Carlin, H.S. Stern, and D.B. Rubin. (1995), *Bayesian Data Analysis*, Chapman and Hall.

Goolsbee, A. and A. Petrin, (2001). "Consumer Gains from Direct Broadcast Satellites and the Competition with Cable TV," *Working paper*.

Gönül, Fusun and Kannan Srinivasan, (1993). "Modeling Multiple Sources Of Heterogeneity In Multinomial Logit Models: Methodological and Managerial Issues," *Marketing Science*, 12 (summer), 213-229.

Hoch, S., B. Kim, A. Montgomery, and P. Rossi, (1995). "Determinants of Store-Level Price Elasticity", *Journal of Marketing Research*, 32 (February).

Huber, J and K. Train, (2003). "On the Similarity of Classical and Bayesian Estimates of Individual Mean Partworths," *Marketing Letters*.

Jain, Dipak C. and Naufel J. Vilcassim (1991) "Investigating Household Purchase Timing Decisions: A Conditional Hazard Function Approach", *Marketing Science*, 10, 1, (Winter) 1-23.

Kadiyali V, Sudhir K, Rao V. R., (2001). "Structural analysis of competitive behavior: New Empirical Industrial Organization methods in marketing." *International Journal of Research in Marketing*, 18 (1-2): 161-186.

Kadiyali, V., P.Chintagunta and N. Vilcassim, (2000). "Manufacturer-Retailer Channel Interactions and Implications for Channel Power: An Empirical Investigation of Pricing in a Local Market." *Marketing Science,* 19(2):127-148.

Kahn, Barbara E. and David C. Schmittlein, (1989). "Shopping Trip Behavior: An Empirical Investigation," *Marketing Letters*, 1, December, 55–70.

Kahn, B. E. and D. C. Schmittlein, (1992). "The Relationship between Purchases Made on Promotion and Shopping Trip Behavior," *Journal of Retailing*, special issue, 68, Fall 1992, pp. 294-315.

Kahn, Barbara E. and Lehmann, Donald R., (1991). "Modeling Choice Among Assortments," *Journal of Retailing*, **67,** Fall, pp. 274–299.

Kahn, B. E. and L. McAlister, (1997). "*Grocery Revolution: The New Focus on the Consumer*," Reading, MA: Addison Wesley, Longman.

Kekre, Sundar and Srinivasan, Kannan, (1990), "Wider Product Line: Is it Necessary to Achieve Success?" *Management Science*.

Krishnan, Trichy, Kitty Koelemeijer and Ram C. Rao, (2002), "Consistent Assortment Provision and Service Provision in a Retail Environment," *Marketing Science*, Vol. 21, No. 1, Winter 2002, pp. 54-73.

Kumar, V. and Robert P. Leone (1988), "Measuring the Effect of Retail Store Promotions on Brand and Store Substitution," *Journal of Marketing Research*, 25, 178–186.

Lattin J.M, and McAlister L., (1985). "Using A Variety-Seeking Model To Identify Substitute And Complementary Relationships Among Competing Products." *Journal of Marketing Research*. 22 (3): 330-339 1985.

McIntyre, Shelby and Miller C, (1999). "The selection and pricing of retail assortments: an empirical approach," *Journal of Retailing*, Volume 75, Issue 3, Autumn 1999.

Narasimhan, C., (1984). "A Price Discrimination Theory of Coupons," *Marketing Science*.

Rossi, Peter E., Robert E. McCulloch and Greg M. Allenby, (1996). "The Value of

Purchase History Data in Target Marketing," *Marketing Science*, 15, 321-340.

Shaffer, Greg and Zhang, John Z., (1995). "Competitive Coupon Targeting." M*arketing Science*, Vol. 14, No. 4. (1995), pp. 395-416.

Shugan, Steven, and Ramarao Desiraju, (2001)."Retail Product-line Pricing Strategy when Costs and Products Change", *Journal of Retailing*, Spring 2001, Vol. 77, No. 1, pp. 17-38.

Simonson, Itamar, (1999) "The effect of product assortment on buyer preferences," *Journal of Retailing*, Volume 75, Issue 3, Autumn 1999, Pages 347-370.

Smith, A F M, and Gelfand, A. E, (1992). "Bayesian Statistics Without Tears - A Sampling Resampling Perspective."*American Stat* 46 (2): 84-88.

Stassen RE, Mittelstaedt JD, Mittelstaedt RA, (1999). "Assortment overlap: Its effect on shopping patterns in a retail market when the distributions of prices and goods are known." *Journal of Retailing* 75 (3): 371-386.

Sudhir, K. (2001), "Structural Analysis of Competitive Pricing in the Presence of a Strategic Retailer," *Marketing Science*, 20, 244.

Urban, Timothy L., (1998). "An Inventory-Theoretic Approach to Product Assortment and Shelf-Space Allocation." *Journal of Retailing,* **74** 1, pp. 14–35.

van Ryzin, G.J. and S. Mahajan, (1999). "On the Relationship Between Inventory Cost and Variety Benefits in Retail Assortments," *Management Science*, 45, 1496-1509.

Villas-Boas, M. and R. Winer (1999), "Endogeneity in Brand Choice Models," *Management Science*, 45, 10, 1324-1338.

Walters, Rockney G. (1991), "Assessing the Impact of Retail Price Promotions on Product Substitution, Complementary Purchase, and Interstore Sales Displacement," *Journal of Marketing*, 55 (April), 17-28.

ESSAY 2

PRICE-LOCATION LINKS IN CONSUMER AND COMPETITIVE CHOICES – AN APPLICATION OF THE GENERALIZED NESTED LOGIT STRUCTURAL ANALYSIS OF RETAIL COMPETITION[15]

Abstract

To study how consumers make tradeoffs in price and location in retail contexts, we estimate a Generalized Nested Logit model (Wen and Koppelman, 2001) of demand. We account for unobserved consumer heterogeneity, and endogeneity in price and location. We also estimate how firm pricing decision rules and the impact of location on firms' cost structure. The empirical application is to hotels in Texas 1991-1997.

1. Introduction

In this essay, we are interested in studying price competition among hotels at pre-specified locations. Industry classification, and hence competitive set definition, of hotels is based on price tiers. However, it appears plausible that location attributes should also matter to the definition of competitive set. For example, a hotel (or property as it is known in the industry jargon) located at a favorable location might be able to charge a price premium relative to a property in the same price tier but at an unfavorable location. And it might be competing more directly with a property in the same location but a different price tier than it does with a property of the same price

[15] An earlier version of this essay was presented at the INFORMS Pricing Conference at Cornell University, August 2002. We thank Pradeep Chintagunta, J.P. Dube, Naufel Vilcassim, K. Sudhir, and seminar participants at Northwestern-Kellogg, NYU-Stern, UCLA-Anderson and UC-Irvine, and conference attendees at INFORM-Pricing 2002 and at Marketing Science 2003, for their comments.

tier at a different location. Location might also affect a property's cost structure, and hence pricing, and hence its competitive set.

To understand better how firms compete when price and location attributes matter, a critical first step is to understand consumer preferences for price and location attributes. In other words, we need to first build a realistic model of consumer choice processes and their tradeoffs among various product attributes including price and location. These demand model estimates combined with a model of how location can influence costs can then form the basis of a supply analysis of firm price setting. We argue in this essay that the results of this exercise are very dependent on the consumer demand formulation, and therefore the appropriate choice model should be chosen to model consumer demand. In particular, we argue that the generalized nested logit (Wen and Koppelman, 2001, GNL hereon) provides a robust tool to examine this problem for our industry and dataset context.

First, the GNL has the advantage of allowing nesting structures in consumer choices, unlike the logit model. More importantly, unlike the nested logit, the GNL allows for endogenous nest estimation. In GNL, any choice alternative can be allocated to multiple nests simultaneously (the sum of all such allocations should of course add up to 100%). This overlapping nests allows the accommodation of correlation in unobserved attributes between members belonging to different nests, which cannot be accommodated in nested logit. Therefore, cross-price elasticities between two alternatives includes both cross-price effects when they are present in the (multiple) same and in the (multiple) different nest. These features of the GNL make it a more appropriate demand specification when attributes tradeoffs and correlation between the utilities of different alternatives are not obvious ex-ante to the researcher.

These advantages of the GNL are especially relevant for our hotel price-location link study for the following two reasons. First, industry studies indicate that while there are clear ideal points for demand (specifically, downtown and airport), the trade-offs in price and distance from these ideal points is not well known. Therefore, there could be some nesting structures in consumer choices that involve complex combinations of price and location. Second, as we will discuss in our data section (data on Texas hotels for various cities over 1991-1997), we only observe price and location attributes of firms (and we know brand names), but there are several other attributes that matter to consumer choices for which we have no information (e.g., shopping arcade, swimming pool, gym etc.). These attributes might be the source of error correlation between alternatives either in the same nest or different nests. Therefore unlike nested logit, for our industry we cannot assume that consumer utility for alternatives belonging to different nests are uncorrelated.

Given these advantages of the GNL for our industry and data, we use it as the demand model. We model consumer utility as being a function of both prices and distances from two ideal points (downtown and airport). Given demand and cost functions, hotel firms choose optimal price (that is, price is strategically and econometrically an endogenous variable). While we do not model location choices of firms (these decisions have already been made prior to our data observation period), we do account for the econometric endogeneity of location.

To anticipate the results, we find location effects to be important both to consumers (and hence to firm revenues), as well as to firms' costs. On average, consumers prefer to be closer to downtown and away from the airport. They are willing to pay \$1.44 to be one mile closer to the central business district, and \$1.22 to be one mile away from the airport. As an illustration of the importance of the right demand specification, we estimate a random-coefficient logit demand specification as well, given the widespread use of this model in (both location and non-location) choice models in marketing and economics. Compared to the proposed model, a mixed logit model a) has poorer fit, b) yields statistically different price location response coefficients, and c) overpredicts consumer heterogeneity.

The computed price elasticities for the GNL demand model exhibit patterns counter to popular industry classifications (example cross price elasticity between Sheraton (a higher priced or "luxury" brand) and Hilton (a middle-price tier or "midscale" brand) (0.71) is higher than the cross price elasticity between Sheraton and Marriott (midscale) (0.66) or Sheraton and Hyatt (luxury) (0.61). We also find that firm costs increase as they move away from downtown and towards the airport. From a substantial standpoint, this study therefore provides evidence for the interdependence of location and price decisions and the sensitivity of results to the estimated demand model used to examine competition in geographically differentiated oligopolies.

In the following sections, we describe our proposed model in more detail (section 2) and contrast it to existing studies, discuss the data (section 3) and the results (section 4). We conclude by summarizing and offering suggestions for future research (section 5).

2. Model

2.1. The rationale for a demand-and-supply model

Starting with Hotelling (1929), there is a large stream of literature theoretical that focuses on how consumers make price-location trade-offs in choosing their retail store location. Consumer makes these choices taking into account their transportation costs to these retail stores and the layout of the geographic space in which they exist (e.g., a linear city or a circular city). Depending on these consumer preferences and geographic layout, retail stores then locate at dispersed points in the geographic space and choose appropriate prices. In making these decisions, retail stores need to account for two opposing forces - locating in an area with higher density of demand might lead to more demand, but an attractive location might also attract other competitors and hence lead to lower profits. In such a model, retail stores compete most with rivals located closest to them. Therefore, the theoretical literature in this area highlights the importance of examining both consumer and firm choices when modeling price-location interactions.

The predictions of these theoretical models on price-location competition have been tested empirically. Despite the fact that theoretical models start with a demand specification, the majority of empirical work in this area does not model demand explicitly. That is, the papers in this area focus on the supply or competition side alone, and characterize the correlation between equilibrium prices and equilibrium locations. For example, Johnson and Parkman (1983) find in their study of cement market that profitability declines as firms locate near one another i.e. negative correlation between price and inter-firm distance. Therefore, they conclude that firms compete most with those located closest to their own location. Haining (1984) finds greater price clustering among neighboring outlets in urban gasoline retailing than among non-neighboring outlets, providing further evidence of price-location interactions in firm decisions. Note however that price clustering can be consistent with both tacit collusion and perfect competition. In Cotterill's (1986) study of the retail food industry in Vermont, distances between retail outlets have negligible effects on their prices, so price appears to be independent of location i.e. no price-location interaction. Here too this lack of effect could be due to perfectly competitive retailer markets, or perfectly collusive ones, or even due to upstream wholesaler power.

Summarizing, these studies examine the correlation between price and location, or price and distance from competitors, and find that the evidence on price-location link is mixed. A concern with all these studies is that we are unable to understand consumer preferences for prices and location, and the tradeoffs between these two. We are also unable to see how firms' profits are influenced by costs of location at a favorable location relative to an unfavorable location. Therefore, in this essay, we model demand and supply-side simultaneously .

In modeling both demand and supply aspects of the location-price link, there is a growing stream of literature. The questions asked here are: what are consumer preferences for price and location and how do these influence firm choices? Do consumers have some ideal points for firm location? How high are transportation costs? Given these preferences and costs, where should firms locate and how should they price? This recent stream of literature comprises papers by Seim (2001), Davis (2002), Kamita (2001), and Thomadsen (2001).

For the purpose of studying the lodging industry (the focal industry for this study), these studies make some assumptions that need to be relaxed. Seim (2001) for example, models where video stores should locate in markets, using a reduced-form profit function. She does not structurally model pricing by firms or consumer choices in this market. Hence her model precludes the possibility of studying consumer preference for price and location and price-location tradeoffs in competitive choices. Additionally, she defines markets exogenously by slicing up her area of study into mutually exclusive and collectively exhaustive cells. This precludes the possibility of studying competition between retail outlets in various locations in a geographic differentiated oligopoly. Similar restrictive market definitions are imposed in the Davis (2002) study on movie theater pricing, Thomadsen (2001) model on the fast-food industry, and Kamita (2001) the trash-hauling industry. Another issue is that these papers use the logit/random coefficients logit demand model. We believe the GNL model is more appropriate to our context than the logit or random coefficients logit for reasons discussed below.

2.2 Modeling Demand

Before we discuss our demand model for our industry (the Texas lodging industry), we first provide some comparison between GNL and other demand models used in research in marketing and economics. There is a long history of utility-based structural demand modeling in marketing (e.g., Guadagni and Little 1983, Kamakura and Russell 1989, Krishnamurthi and Raj 1991, Chintagunta 1993). Early choice models assumed that the error terms were multivariate normal or independently and identically Type I extreme value (Gumbel) distributed (Johnson and Kotz, 1970). The multivariate normal error distribution assumption leads to the multinomial Probit (MNP) model (Daganzo, 1979) while the i.i.d. Gumbel assumption leads to the multinomial logit (MNL) model (McFadden, 1973). MNL and its variants are the most widely used in marketing. It is derived from first principles of utility maximization and its simple mathematical structure facilitates ease of estimation. However its independence of irrelevant alternatives property (IIA), leads to incorrect predictions due to MNL's unrealistic restriction on the cross price elasticities between alternatives. The probit model allows complete flexibility in the variance covariance structure of the error terms but requires numerical integration of a multivariate normal distribution. The nested logit model, which allows interdependence between pairs of alternatives in a common group, is a widely known relaxation of the MNL, while retaining the closed form solution.

An issue with the multinomial Probit model is the lack of closed form solutions and the resulting computational burden in estimation. Developments have been directed at reducing the computational burden associated with the model (McFadden, 1989; Hajivassiliou and McFadden, 1990; Börsch Supan and Hajivassiliou, 1992; Keane, 1994, Chintagunta, 2001). Additionally, the use of random coefficients in multinomial logit and nested logit models using aggregate data not only incorporates heterogeneity in consumer preferences but also relaxes the IIA restriction (Sudhir 2001, Nevo 2000). Despite all this, for our purposes, the mixed logit might not offer the required level of flexibility of substitution patterns given the unique features of hotel choices and data discussed in the introduction.

Another area of exciting methodological developments in recent years has been in the class of Generalized Extreme Value (GEV) models. These developments have resulted in a number of new model forms that retain a closed form expression for choice probabilities, but offer much greater flexibility in the specification of the correlation structure of the errors. In particular, consider the GNL, which allows for complex substitution patterns between alternatives. The homogeneous GNL proposed by Wen and Koppelman (2001), is derived from McFadden's (1978) generalized extreme value (GEV) model. Like the nested logit it allows error terms between alternatives in a nest to be correlated. The common error component across alternatives in a nest alleviates the IIA property of the MNL within nests. This feature of the GNL is similar to NL. In NL, an alternative is present in only one nest, allowing for error correlation between alternatives within a nest but not between alternatives belonging to different nests.

However a situation often encountered in practice is that alternatives in different nests share some unobserved attributes, making the across nest error correlation assumption of the NL very restrictive (Train, 2003). For example attributes like on-site shuttle, gym, pool etc. can be shared by alternatives belonging to different nests. However, these attributes are unobserved by the econometrician and can be a source of error correlation between alternatives belonging to different nests. The need for realistic representations of such choice situations has spawned developments in discrete choice models like GNL that allow for overlapping nests.

The overlapping nests feature allows for non-zero error correlations between alternatives both within and across nests. As an example, consider a choice set with four alternatives (1,2, 3 and 4). Assume alternatives 2 and 3 are similar to alternative 1 in some attribute and to alternative 4 in another. The standard nested logit cannot represent this structure because alternative 2 is present in both nests. The GNL can allow a configuration of nests like nest 1 comprising (1,2,3) and nest 2 comprising (2,3,4) where alternatives 2 and 3 are present in both nests. Furthermore, the GNL allows for alternatives to be present in varying degrees (through *fractional allocation parameters*) in each nest[16]. That is, continuing with the previous example, the GNL allows the following: alternative 2 is allocated 20% to nest 1 (1,2,3) and 80% to nest 2 (2,3,4) at the same time that alternative 3 is allocated 75% to nest 1 (1,2,3) and 25% to nest 2 (2,3,4). The GNL also estimates logsum parameters associated with each nest that are interpreted as how similar or dissimilar members of a nest are.

Since the within nest elasticities are functions of the fractional allocation parameters, GNL allows for the pair-wise elasticity between two alternatives (say alternatives 2 and 3 in our example) to be different in different nests (in nest 1 and 2 in our example), a unique feature of GNL. The overall pair-wise elasticity between alternatives (alternatives 2 and 3 in our case) accounts for both within nest and across nest (nests 1 and 2 in our example) presence. Therefore it accommodates differential cross-price elasticities across pairs of alternatives both within and across nests[17]. This feature of the GNL makes it appealing for several situations in which nest membership is not obvious and/or if data contain information on only a subset of attributes used by consumers to make their choice.

Comparing the GNL to other discrete choice models, the GNL does not suffer from the IIA property of the logit. However unlike the probit, it has closed form solutions for individual level choice probabilities. GNL nests MNL, NL (special case) and

[16] The cross-nested logit (CNL) model (Vovsha, 1997) allocates a fraction of each alternative to a set of nests with equal logsum parameters across nests; the product differentiation (PD) model (Bresnahan et al, 1997) allocates each alternative to one nest along each of a set of pre-selected dimensions with allocation parameters associated with each dimension with equal logsum for nest in the same choice dimension.

[17] The allocation parameters within a nest are driven by combination of attribute levels of the alternatives in the nest and attributes unobserved in the model. Detailed explanation for this is presented later in this section.

other nested variants. We propose a random coefficients GNL demand model, to account for unobserved consumer preference and error heterogeneity not accounted in Wen and Koppelman (2001)[18].

We now turn to the application of GNL to hotel demand. Although the data we observe are annual sales of room nights, we motivate and estimate the demand model assuming discrete choice behavior at the individual level. We use a technique developed in economics by Berry et al. (1995) and later used in marketing studies like Sudhir (2001), Chintagunta (2001) and Besanko et al. (1998). Here a consumer chooses a property from the available set of properties. The unit of demand is assumed to be a room-night [19]. When the individual demand is aggregated across all consumers within a year, we obtain the annual sales of room nights for each property. Thus, at the aggregate level the unit of observation is property level market shares where a market is defined as a city-year, implying that any property in a city can compete with any other, and not just those in the same geographic or price band (contrast this to the more restrictive market definitions in Seim (2001) or Davis (2002) where a market is defined as a pre-specified geographic area.

On each travel occasion to a given market, a consumer selects a property from the available set of properties based on brand name, price per room night, and its geographic location; all properties in a city-year market are included in the choice set.

[18] Swait (2000) proposes the Generalized MNL model, to simultaneously evaluate choice and choice set generation. The GenMNL model is identical to the GNL except that the allocation parameters are constrained to be equal. The interplay between consumer choice and choice set formation is not the focus of this paper as is the case in Swait (2000). However accounting for choice set generation would be an interesting extension for future research in this area.

[19] At the individual level, consumers may buy multiple room nights on a travel occasion. In aggregate data we are unable to account for this behavior and have to treat the multiple units as independent discrete choices, resulting in a possible bias in the demand estimates. Similar discrete choice assumptions have been made in Sudhir (2001) and Chintagunta (2001).

Literature on the hospitality industry (e.g. Wall et al. 1985) indicates that travelers, who are the primary consumers of lodging services, prefer hotels that are located at one of two locations - central business district (CBD) and airport (AIR). We treat these two locations as ideal points of consumers[20]. Contrast this specification of distance from an ideal point to the more common specification of distance from a latitude-longitude intersection used in Seim (2001), Davis (2002), etc. In our industry, it is unlikely that consumers will value all locations on a latitude-longitude grid equally, thereby making our ideal point specification more appropriate than the ones employed in the studies mentioned above.

Specifically, the choice process for consumer i involves selecting among $h = 1,....,H_m$ hotel properties in market $m = 1,...,M$. The indirect utility that consumer i derives from a room-night in hotel h in market m is given by

$$U_{ihm} = \gamma_{hm} - \alpha p_{hm} + g(d_{hCBDm}, d_{hAIRm}) + \xi_{hm} + \varepsilon_{ihm} \tag{1}$$

where γ_{hm} is the property constant, α is the marginal utility of price; $g(.)$ is the transportation cost function; ξ_{hm} reflects factors that affect the consumer's utility from h in market m but are unobserved by the researcher, and ε_{ihm} is a mean zero stochastic term. ξ's include numerous hotel characteristics like external appearance, residence services such as gym, laundry, shuttle service etc., temporary construction or blockade

[20] We are limited by available data to these four attributes. It is possible that consumers have other ideal points. For example, for one city it might be beach-front properties, for another it might be a technology park in a suburb; in fact, some cities might have several ideal points. Given these likely differences across cities, for any additional ideal point specification, trying to find a centroid to define as that ideal point (should it be the middle of the beach-front strip, or the edge of the technology park?) would be ad-hoc. Therefore, we postulate that should these other ideal points exist, they are currently captured in the error term. As explained later, the GEV error term distributional assumptions are general (unrestrictive) enough for this to not cause a problem.

of highway exits that lead to the property, resulting in reduced access, and hence utility to the consumer, and so forth. Note that these property-specific factors in each market are unobservable to us in the data but observable to both the consumer and the firm. Therefore price *p* might be correlated with the unobserved factors that affect demand, causing econometric endogeneity of price. Choice of property location might also be affected by ξ, for example, proximity to highway exits and recreational facilities. Thus like price, correlation between unobserved factors and geographic location causes endogeneity in location choice. In this respect, we depart from existing papers that assume location to be econometrically exogenous (e.g., Kamita 2001, Davis 2002, and Thomadsen 2001).

The transportation cost function *g(.)* depends on two variables - distance of property *h* from airport and from CBD in market *m*, denoted as d_{hAIRm} and d_{hCBDm} respectively.[21] Following Huff (1966) and Anderson and De Palma (1992) we specify a linear quadratic transportation cost function as below

$$g(d_{hCBDm}, d_{hAIRm}) = -\phi_1 * d_{hCBDm} + \phi_2 * d^2_{hCBDm} - \phi_3 * d_{hAIRm} + \phi_4 * d^2_{hAIRm} \qquad (2)$$

We postulate that the disutility from choosing a property increases at a diminishing rate in distance from the consumer's ideal point. This concavity in consumer disutility is modeled as a quadratic transportation cost function, and ensures an internal solution (Anderson and dePalma, 1992). Combining equations (1) and (2) we get

$$U_{ihm} = \gamma_{hm} - \alpha p_{hm} - \phi_1 d_{hCBDm} + \phi_2 d_{hCBDm}{}^2 - \phi_3 d_{hAIRm} + \phi_4 d_{hAIRm}{}^2 + \xi_{hm} + \varepsilon_{ihm} \qquad (3)$$

[21] We do not impose a linear city structure. Therefore, specifying the distance of any property from any one ideal point does not uniquely describe the location of any property.

This utility specification is a simple extension to single ideal point parameterizations, to accommodate multiple ideal points. In our case, airport and CBD are the ideal points. One should note that in several studies (Hauser and Shugan 1983; Hauser 1988; Choi, DeSarbo and Harker, 1990, 1992), the consumers' ideal point/points are endogenously determined in their proposed model. In our study they are fixed and exogenous based on industry surveys mentioned previously.

To complete the demand specification, we formulate the utility from the outside good as follows::

$$U_{iom} = \varepsilon_{iom} \tag{4}$$

Equation (3) implicitly assumes a set A_{hm} of consumers who select alternative h in market m, where A_{hm} is given by

$$A_{hm} = \{(\varepsilon_{iom}, \varepsilon_{i1m}, \varepsilon_{i2m}, \varepsilon_{i3m}, \varepsilon_{i4m}, ..., \varepsilon_{ihm}, ..\varepsilon_{iHm}) : U_{ihm} \geq U_{ilm}, \forall l \neq h\} \tag{5}$$

Assuming ties occur with zero probability the market share of property h in market m can be expressed as

$$S_{hm} = \int_{A_{hm}} dP^*(\varepsilon) \tag{6}$$

where $P^*(\varepsilon)$ denotes population distribution function for the stochastic demand shock ε.

Next we discuss the homogenous GNL model followed by the heterogeneous GNL model. GNL is consistent with a utility maximizing decision theoretic approach under some conditions as described in the next section.

Model I: Homogenous Generalized Nested Logit Demand Model

The GNL is a GEV model derived from the p.d.f for

$$F(\varepsilon_1,\varepsilon_2,\varepsilon_3,\ldots\varepsilon_J)=\sum_n\left(\sum_{j\in N_n}(a_{jn}e^{V_j})^{\frac{1}{\mu_n}}\right)^{\mu_n} \tag{7}$$

where n denotes nest and N_n is set of alternatives in nest n. Making the assumption of GNL for the ε_{ihm} and we obtain the expressions for aggregate shares given by

$$S_{hm}=\sum_n S_{hm/n}\times S_{nm}=\sum_n\left[\frac{\left(a_{hn}\ \mathrm{e}^{V_{\text{ihm}}}\right)^{\frac{1}{\mu_n}}}{\sum_{j\in N_n}\left(a_{jn}\ \mathrm{e}^{V_{\text{ijm}}}\right)^{\frac{1}{\mu_n}}}\times\frac{\left(\sum_{j\in N_n}\left(a_{hn}\ \mathrm{e}^{V_{\text{ijm}}}\right)^{\frac{1}{\mu_n}}\right)^{\mu_n}}{\sum_{n'}\left(\sum_{j\in N_{n'}}\left(a_{jn'}\ \mathrm{e}^{V_{\text{ijm}}}\right)^{\frac{1}{\mu_{n'}}}\right)^{\mu_{n'}}}\right] \tag{8}$$

where N_n is the set of all alternatives included in nest n, a_{hn} is the allocation parameter which characterizes the portion of alternative h assigned to nest n. If allocation parameter is zero or econometrically insignificant for any alternative in any nest, it signifies that the alternative does not belong in that nest. A value of one indicates that this alternative is not fractionally allocated but rather only belongs in a single nest. The share in nest n of alternative h in market and share of nest n in market m are given by the expressions below

$$S_{hm/nm}=\left[\frac{\left(a_{hn}\ \mathrm{e}^{V_{\text{ihm}}}\right)^{\frac{1}{\mu_n}}}{\sum_{j\in N_n}\left(a_{jn}\ \mathrm{e}^{V_{\text{ijm}}}\right)^{\frac{1}{\mu_n}}}\right] \tag{9}$$

$$S_{nm}=\left[\frac{\left(\sum_{j\in N_n}\left(a_{hn}\ \mathrm{e}^{V_{\text{ijm}}}\right)^{\frac{1}{\mu_n}}\right)^{\mu_n}}{\sum_{n'}\left(\sum_{j\in N_{n'}}\left(a_{jn'}\ \mathrm{e}^{V_{\text{ijm}}}\right)^{\frac{1}{\mu_{n'}}}\right)^{\mu_{n'}}}\right] \tag{10}$$

a_{hn} must satisfy the condition that $\sum_n a_{hn} = 1 \ \forall \text{h}$ [22]. μ_n is the logsum parameter that captures the dissimilarity between alternatives in nest *n*. The GNL model is consistent with random utility maximization if the condition $0 \le \mu_n \le 1$ (for all n) is satisfied. A high value for this parameter means alternatives in a nest are dissimilar, and low value means alternatives in the nest are similar.

The cross price effect of share of alternative *h* with respect to price of alternative *k* is given by

$$-\left\{ S_{hm} + \sum_n \left[\frac{1-\mu_n}{\mu_n} \right] \frac{S_{nm}\left(S_{hn|nm} * S_{kn|nm}\right)}{S_{km}} \right\} \alpha S_{km} \qquad (11)$$

Note that the elasticity expression is a function of nest logsum parameter and allocation parameters (via shares). When the logsums are all set to be equal to 1, the above equation simplifies to the cross-elasticity expression for multinomial logit. Under the restriction that alternatives belong to only one nest and the allocation parameters sum to 1, the above expression simplifies to the cross-elasticity expression for nested logit.

Therefore, once we estimate the nest allocations we can get a better understanding of the consumers' decision process. Furthermore, given nest overlap, at the aggregate/industry level we can examine how each alternative is positioned relative to others in each nest.

[22] Note, the allocation parameters of alternatives across nests do not have any explicit structural interpretation. They are best viewed as the population level likelihood or probability of the alternative in a nest.

Full Model – Generalized Nested Logit With Consumer Heterogeneity (or mixed GNL)

In practice consumers might differ in their preference for price and location. We therefore extend the homogenous GNL model by introducing consumer specific taste parameters. Berry et al. (1994) demonstrate the advantages of incorporating consumer heterogeneity using a random coefficients approach; their application is to the logit model of consumer choices. Following them, we also incorporate consumer heterogeneity via random coefficients or individual-specific taste parameters in the consumer utility specification. This is done despite using aggregate data. The extant literature in this area employs both continuous parametric distribution and discrete support for the random coefficients distribution. We use a continuous support random coefficients demand model, and draw the consumer specific taste parameters from an empirical distribution (Nevo 2001). We chose the continuous support approach over the latent class/discrete support approach to reduce the number of estimated parameters[23]

Re-specifying the utility function as a function of individual taste parameters, we have

$$U_{ihm} = \gamma_j^i - \alpha^i p_{hm} - \phi_1^i d_{hCBDm} + \phi_2^i d_{hCBDm}^2 - \phi_3^i d_{hAIRm} + \phi_4^i d_{hAIRm}^2 + \xi_{hm} + \varepsilon_{ihm} \qquad (12)$$

where $\gamma_j^i, \alpha^i, \phi_1^i, \phi_2^i, \phi_3^i$ and ϕ_4^i are individual specific taste coefficients. The ξ's and ε's are as discussed previously.

[23] Additionally, there might be some segment identification problems using aggregate data as demonstrated in Bodapati and Gupta (2004).

Assuming continuous support for consumer heterogeneity, we integrate the individual level choice probabilities (in the homogenous case this is equivalent to market share expressions) in Model 1, over its continuous support. However, unlike Nevo (2000), consumers in our industry are transient to the local market, and therefore we cannot use the local demographics' distribution to model consumer heterogeneity. Instead, like Besanko et. al. (2003), we rely on draws from a parametric distribution. Since we do not observe individual level choices, we simulate individual choice probabilities by drawing the individual taste heterogeneity parameters as follows

$$\begin{pmatrix} \gamma^i \\ \alpha^i \\ \phi_1^{\ i} \\ \phi_2^{\ i} \\ \phi_3^{\ i} \\ \phi_4^{\ i} \end{pmatrix} = \begin{pmatrix} \gamma \\ \alpha \\ \phi_1 \\ \phi_2 \\ \phi_3 \\ \phi_4 \end{pmatrix} + \begin{pmatrix} \varsigma_{\gamma i} \\ \varsigma_{\alpha i} \\ \varsigma_{\phi_1 i} \\ \varsigma_{\phi_2 i} \\ \varsigma_{\phi_3 i} \\ \varsigma_{\phi_4 i} \end{pmatrix}$$

and error heterogeneity parameters $\boldsymbol{\mu}_\mathbf{n} \sim N(\bar{\boldsymbol{\mu}}_\mathbf{n}, \boldsymbol{\sigma}_{\boldsymbol{\mu}_\mathbf{n}})$ (13)

where $\gamma, \alpha, \phi_1 - \phi_4$ are the population level mean preference parameters and $\bar{\boldsymbol{\mu}}_\mathbf{n}$ is the vector of population level mean error parameters

$$\varsigma_{\bullet i} = N(0, \sigma_\bullet^2) \tag{14}$$

Respecifying the utility function as a function of population mean and individual taste variation parameters, we have

$$U_{ihm} = V_{hm} + \varsigma_{\gamma^i} - \varsigma_{\alpha^i} p_{hm} - \varsigma_{\phi 1^i} d_{hCBDm} + \varsigma_{\phi 2^i} d_{hCBDm}^2 - \varsigma_{\phi 3^i} d_{hAIRm} + \varsigma_{\phi 4^i} d_{hAIRm}^2 + \varepsilon_{ihm} \tag{15}$$

where $$V_{hm} = \gamma - \alpha p_{hm} - \phi_1 d_{hCBDm} + \phi_2 d_{hCBDm}^2 - \phi_3 d_{hAIRm} + \phi_4 d_{hAIRm}^2 + \xi_{hm} \tag{16}$$

Thus the individual choice probability expressions are given below:

$$P_{ihm} = \sum_n P_{ihm/nm} \times P_{inm} = \sum_n \left[\frac{\left(a_{hn} \ \mathrm{e}^{V_{\mathrm{ihm}}}\right)^{\frac{1}{\mu_n}}}{\sum_{j \in N_n} \left(a_{jn} \ \mathrm{e}^{V_{\mathrm{ijm}}}\right)^{\frac{1}{\mu_n}}} \times \frac{\left(\sum_{j \in N_n} \left(a_{hn} \ \mathrm{e}^{V_{\mathrm{ijm}}}\right)^{\frac{1}{\mu_n}} \right)^{\mu_n}}{\sum_{n'} \left(\sum_{j \in N_{n'}} \left(a_{jn'} \ \mathrm{e}^{V_{\mathrm{ijm}}}\right)^{\frac{1}{\mu_{n'}}} \right)^{\mu_{n'}}} \right] \tag{17}$$

The conditional choice probability (alternative choice probability conditional on nest choice) and probability of nest choice respectively are given by the expressions below

$$P_{ihm/nm} = \left[\frac{\left(a_{hn}\ \mathrm{e}^{V_{\mathrm{ihm}}}\right)^{\frac{1}{\mu_n}}}{\sum_{j\in N_n}\left(a_{jn}\ \mathrm{e}^{V_{\mathrm{ijm}}}\right)^{\frac{1}{\mu_n}}} \right] \tag{18}$$

$$P_{inm} = \left[\frac{\left(\sum_{j\in N_n}\left(a_{hn}\ \mathrm{e}^{V_{\mathrm{ijm}}}\right)^{\frac{1}{\mu_n}}\right)^{\mu_n}}{\sum_{n'}\left(\sum_{j\in N_{n'}}\left(a_{jn'}\ \mathrm{e}^{V_{\mathrm{ijm}}}\right)^{\frac{1}{\mu_{n'}}}\right)^{\mu_{n'}}} \right] \tag{19}$$

Summing over all simulated individuals *i* in market *m* we obtain the simulated market share expression for alternative *h* in market *m* as given below

$$\boldsymbol{S}_{hm} = \frac{1}{N_{sm}} \sum_{i=1:n_{sm}} \left[\sum_{n} \left[\frac{\left(a_{hn}\ \mathrm{e}^{V_{\mathrm{ihm}}}\right)^{\frac{1}{\mu_n}}}{\sum_{j\in N_n}\left(a_{jn}\ \mathrm{e}^{V_{\mathrm{ijm}}}\right)^{\frac{1}{\mu_n}}} \times \frac{\left(\sum_{j\in N_n}\left(a_{hn}\ \mathrm{e}^{V_{\mathrm{ijm}}}\right)^{\frac{1}{\mu_n}}\right)^{\mu_n}}{\sum_{n'}\left(\sum_{j\in N_{n'}}\left(a_{jn'}\ \mathrm{e}^{V_{\mathrm{ijm}}}\right)^{\frac{1}{\mu_{n'}}}\right)^{\mu_{n'}}} \right] \right] \tag{20}$$

where N_{sm} is the number of simulated individuals for market *m*. The corresponding share in nest and nest share expressions are as follows

$$\boldsymbol{S}_{hm/nm} = \frac{1}{N_{sm}} \sum_{i=1:ns} P_{ihm/nm} \tag{21}$$

$$\boldsymbol{S}_{nm} = \frac{1}{N_{sm}} \sum_{i=1:ns} \left[\frac{\left(\sum_{j\in N_n}\left(a_{hn}\ \mathrm{e}^{V_{\mathrm{ijm}}}\right)^{\frac{1}{\mu_n}}\right)^{\mu_n}}{\sum_{n'}\left(\sum_{j\in N_{n'}}\left(a_{jn'}\ \mathrm{e}^{V_{\mathrm{ijm}}}\right)^{\frac{1}{\mu_{n'}}}\right)^{\mu_{n'}}} \right] \tag{22}$$

To summarize, equation (20) represents the system of estimation equations for the demand side. That is, we will estimate a GNL-based market share model using aggregate data. We simulate individual level choices using the GNL demand specification, and these individual level choices are aggregated to generate predictions for market share. We account for individual heterogeneity in two separate ways in equation (13): (1) preference heterogeneity via the parameters $\gamma, \alpha, \phi_1 - \phi_4$. This captures heterogeneity in consumer preference for attributes (2) we also allow for heterogeneity among consumers in their evaluation of the similarity among alternatives in a nest. That is, we allow for error heterogeneity (Swait and Bernardino (2000), Kamakura et al. (1996)) in the each of the *n* logsum parameters μ_n. Error heterogeneity enables more flexible patterns in competition between alternatives. Our specification allows for two sources of differential correlation between alternatives belonging to different nests – allocation parameters and consumer varying log-sum parameter. [24]

2.3. __Modeling cost__

We assume that the (annual, given frequency of data) marginal cost per room for property *h* is a function of property-specific cost shifters and a random cost shock. In order to account for location specific cost effects, we specify the marginal cost function as

$$\begin{aligned} mc_{hm} = {} & \omega_h + \kappa_1 * I_h * elect_{hm} + \kappa_2 * I_h * serv_{hm} + \rho_1 * d_{hCBDm} + \rho_2 * d^2_{hCBDm} \\ & + \rho_3 * d_{hAIRm} + \rho_4 * d^2_{hAIRm} + \upsilon_{hm} \end{aligned} \tag{23}$$

where ϖ_h is the property-specific mean component of the marginal cost, I_h is a property-specific dummy and ν_{hm} a mean zero stochastic shock. We include two exogenous marginal costs drivers - electricity costs and service costs. These are price

[24] Consumer choice/decision rule heterogeneity is another possible source of consumer heterogeneity (see Swait and Bernardino (2000)). While Kamakura et al. (1996) account for taste and structural heterogeneity, we do not in this paper. Rather, like Swait and Bernardino (2000), we account for taste and error heterogeneity.

indices that capture the costs of electricity usage and labor/service costs like cleaners, security personnel etc. Note that in the estimation the intercept and the exogenous marginal cost drivers are estimated at the brand level, i.e., all properties of a particular brand have the same parameter. In other words, we model marginal costs that vary by brand. For example higher priced brand might have higher service and utility costs for their properties.

In addition to the above components of marginal cost, we also include a location-based component of marginal cost. This specification allows distance of a property from market foci to affect its marginal costs. Like the transportation costs in the consumer utility specification, here too we specify a quadratic cost function to allow for non-linear effects as firms move away from ideal points. Costs can be related to distance from ideal points for a number of reasons. For example, hotels might need to offer additional services like shuttle service to downtown and airport, luggage check-in, additional dining alternatives etc. to attract location-sensitive consumers. These additional service offerings increase marginal costs for the property. It is also possible, and even likely, that consumer ideal points attract a cluster of competitors, and hence creates a common labor market or lower delivery costs for suppliers (Hannan and Freeman, 1977; Baum and Haveman, 1997).

The stochastic marginal cost error term captures cost shocks (e.g. due to travel shuttle service costs, refurnishing, new on-site features) that are unobserved to the econometrician but known to the firm. We assume that ν_{hm} is independent of ε_{ihm}.

2.4 ***Modeling competition***

We model pricing decisions of firms in this differentiated market, taking as given the locations of their hotel properties. Of course, location was chosen strategically by each of these properties when they entered the market. However, as our time-series data has only three instances of entry, we are unable to estimate a model of entry and endogenous location. Therefore, for any given property, the location is taken to be exogenous for the data period. As we have argued in the section 2.1 above, location is econometrically endogenous, even if it is strategically exogenous, so we will still have to control for this endogeneity in the estimation of demand and supply. Price, on the other hand, is strategically endogenous. That is, firms choose prices taking into account their competitors' choice of actions. We model this interaction as a Bertrand-Nash game.

In the data, firms have multiple properties in each market. Therefore, the pricing and location decisions of firms are modeled as the outcome of maximization of product line profits by hotel firms. Suppose there exist $\boldsymbol{F}$ firms in each market, each managing some N_{fm} of the, H_m properties. $\boldsymbol{H_{fm}}$ is a set of properties owned or managed by firm f in market m. Since the available data are annual, we make the assumption of annual decisions of price[25].

The product line profit function for firm f in market m over all its properties h is given by

$$\pi_{fm} = \sum_{h \in \boldsymbol{H}_{fm}} (p_{hm} - mc_{hm}) \boldsymbol{S}_{hm} M_m \tag{24}$$

[25] Although we see practically no exits or entries, we do see some ownership changes in properties, which acts as another source of location variation within a market over the years observed. Of course, there are variations in locations across markets.

where $\boldsymbol{S}_{hm}$ = share of property h in market m, M_m is the size of market m. mc_{hm} is the constant marginal costs of production/operation of property h. Note, the market size includes the outside good.

Differentiating the profit function with respect to price, we obtain price first-order conditions as follows:

$$\frac{d\left[\left(p_{hm}-mc_{hm}\right)M_m\boldsymbol{S}_{hm}\right]}{dp_{hm}}+\sum_{z\in\boldsymbol{H}_{fm},z\neq h}(p_{zm}-mc_{zm})M_m\frac{d\boldsymbol{S}_{zm}}{dp_{hm}}=0 \tag{25}$$

or

$$\left(p_{hm}-mc_{hm}\right)\frac{d\boldsymbol{S}_{hm}}{dp_{hm}}+\boldsymbol{S}_{hm}+\sum_{z\in\boldsymbol{H}_{fm},z\neq h}(p_{zm}-mc_{zm})\frac{d\boldsymbol{S}_{zm}}{dp_{hm}}=0 \tag{26}$$

where $\boldsymbol{H}_{fm}$ is the set of properties belonging to firm f in market m. This yields the following expression for property h in market m

$$p^*_{hm}=mc_{hm}+\frac{\frac{1}{ns_m}\sum_{i=1:N_m}P_{ihm}+\sum_{z\in\boldsymbol{H}_{fm},z\neq h}(p_{zm}-mc_{zm})\left(\frac{1}{ns_m}\sum_{i=1:N_m}\frac{d}{dp_{hm}}P_{izm}\right)}{\left(\frac{1}{ns_m}\sum_{i=1:N_m}\frac{d}{dp_{hm}}P_{ihm}\right)} \tag{27}$$

where the second term in the equation is the markup for property h in market m, and α is the price response parameter. Using standard empirical IO assumptions, marginal costs are not observed. We rely on obtaining consistent estimates of the demand system and on the equilibrium assumption to compute the marginal costs implied by (23). Like Newey and McFadden (1994) we estimate the model in two stages -- demand model in stage one and supply model in the second stage. The advantages of this approach are three-fold. First, because equilibrium is not enforced in the demand estimation procedures, consistency of demand parameter estimates is independent of the particular equilibrium assumptions made and is therefore robust to a wide set of possible assumptions. Second, there is no need to solve the equilibrium pricing problem during demand model estimation, thereby greatly reduces the computational burden of the estimation procedures involved with estimating the proposed non-linear demand model. The disadvantage of the approach is that greater efficiency could be obtained in the estimates by enforcing equilibrium during estimation[26]. Third, the two-stage estimation procedure employed here does not require us to posit any distributional assumption on ξ in the consumer utility specification, as done in Villas-Boas and Zhao (2003) study where the demand and supply side are jointly estimated.

3. Data

The model is applied to the Texas lodging industry. The Texas State Comptroller requires every lodging property to report taxable and non-taxable revenues on a quarterly basis. Source Strategies Incorporated (SSI), an independent marketing research firm located in San Antonio, aggregates and augments this (public) information in their annual reports entitled Texas Hotel Performance Factbook. We use data on all lodging properties (i.e., hotels, motels, bed-and-breakfasts) in Texas with annual revenues over 13,000 dollars (these properties have to report information to the State Comptroller) from 1991 through 1997.

Hotel brands are categorized into sectors (Full-Service, Limited-Service or Extended Stay) and segments (Deluxe, Luxury, Upscale, and Midscale with Food and Beverage, Midscale without Food and Beverage, Economy, Budget, Upper-tier Extended Stay and Lower-tier Extended Stay). In this study, we focus on full-service sector hotels.

---

[26] In a joint estimation framework, the supply side equations involve implicit functions and computation of the Jacobian, adding more complexity to the estimation procedure.

Full service sector hotels are "usually high-rise establishments, offering a full range of on-premises food and beverage service, cocktail lounge, entertainment, conference facilities, shops and recreational activities. Wide range of services provided by uniformed staff on duty 24 hours. Parking arrangements vary." [27] We limit our analysis to the full service sector for two reasons. One, there are numerous entries and exits in other industry segments, which are outside the scope of this essay. Second, there are no franchised properties in this segment of hotels. Therefore the profit maximization assumption is robust to any agency issues. Interestingly, we also find that airport and CBD properties are predominantly full-service.

We used data from seven of the large cities in Texas, namely Austin, Dallas, Houston, Galveston, Midland, San Antonio, and Waco. We chose these cities for two reasons: a) their large size and b) presence of the focal brands in these cities in all years observed in our data. We define a market as a city-year combination, which results in 7 cities* 7 years = 49 markets. There were 18 properties in the data that exited the market after the data were collected in 1997, hence we could not obtain location information for these observations. Since the number and market share of these properties were not large enough to alter the results substantially, we dropped these properties from the estimation sample. In order to account for vertical and horizontal differentiation within the estimation sample we selected eight brands that represent the three major sub-categories namely Luxury (Hyatt, Marriott, Sheraton), Upscale (Hilton, Courtyard) and Midscale (Ramada Inn, Howard Johnson, Holiday Inn) of the full service category. The final sample consists of 1024 observations that account for 87% of total full-service property shares.

---

[27] Quoted from the AAA. "New York TourBook". Buffalo, NY: AAA Publishing. 1999.

In addition to information on property name, capacity, and revenue, SSI's Factbooks contain information on each property's average daily rates (ADR), brand affiliation and the number of days the property is open throughout the year. ADR is estimated from surveys conducted by SSI, financial reports, information from appraisers, chain and AAA directories, and information provided by Smith Travel Resource. The ADR is the pre-sales tax price[28]. The data required to estimate the model include market shares, prices, brand characteristics, and distribution of population characteristics. Therefore, we augment the property level data with city-county level information including the indices for electric utilities and construction; these last two data series are to be used as marginal cost drivers[29].

For each property we also collect location information via Mapquest.com. Given the street address of a property, we obtained the driving distance in miles and driving time in minutes from two fixed loci - the airport, and the CBD. The correlations between distance and time measures were 0.83 and 0.91 for CBD and airport respectively. Hence we use distance rather than driving time measures to estimate the models.

Some additional issues arise in the implementation of the model to the data. First, in the context of hotel demand, it is not obvious what no-purchase means. For example, it could be consumers who visit the town but do not stay in a lodging facility, but data for this measure is hard to obtain. Moreover, there are multiple ways of translating number of visitors to hotel room demand (e.g., does each visitor translate to one room or double occupancy?) Therefore in this study we treat the no-purchase option to be

[28] Like Sudhir (2001) and Berry et al. (1995), our price measure is the average/aggregate price offered to consumers in a particular market.
[29] We cannot use these cost instruments in demand formulation, given demand is from non-local consumers.

the purchase of a non-focal brand property in the full-service sector. Total market size is defined as the sum of the outside and inside goods for a city-year market. Second, given we have only seven annual observations per property, allocation parameters are estimated at brand level rather than property-level to conserve degrees of freedom.

Table 2.1 contains descriptive statistics of the final estimation sample. Note that there is significant variation in location and price in a market. To determine if the hotels can simply be classified as CBD or AIR type, we divided the sample into two sub-samples, one consists of properties closer to CBD than to the airport, and the other consists of properties that are closer to airport than CBD. Table 2.2 contains descriptive statistics for the two sub-samples. The data indicate that there is significant variation in both location and price within each sub-group. Similarly, we group all the properties into low and high prices based on a median-split, and Table 2.3 contains these descriptive statistics. As is obvious from tables 2.2 and 2.3, a simple price and location split still leaves a lot of heterogeneity in samples. This provides prima facie support for using the GNL demand model. Finally, table 2.4 shows brand-level variance in prices and average distances to indicate that brands clearly price differently depending on demand and competitive conditions in markets; our essay attempts to capture these demand and competition drivers.

Table 2.1 - Descriptive Statistics

Variable	Mean	Std.Deviation
Market Share	0.050	0.043
Price per room night (in US dollars)	74.14	21.49
Distance to CBD (in miles)	7.56	5.94
Distance to Airport (in miles)	7.89	6.43
Room nights sold (in a year)	86703	21004

Table 2.2 - Descriptive statistics by price range

Variable	High price hotels Mean	Std.Dev	Low price hotels Mean	Std. Dev
Market Share	0.071	0.022	0.024	0.016
Price per room night (in US dollars)	79.04	12.56	64.56	9.75
Distance to CBD (in miles)	7.42	5.45	5.33	4.34
Distance to Airport (in miles)	6.84	6.47	6.01	3.22
Room nights sold (in a year)	61022	11087	50034	12091

Table 2.3 - Descriptive statistics by distance

Variable	Hotels closer to CBD Mean	Std.Dev	Hotels closer to AIR Mean	Std. Dev
Market Share	0.047	0.043	0.067	0.069
Price per room night (in US dollars)	64.474	24.597	78.316	23.093
Distance to CBD (in miles)	3.546	3.039	12.226	6.535
Distance to Airport (in miles)	7.61	8.533	3.632	2.704
Room nights sold (in a year)	72360.52	15180.19	71258.93	35725.3

Table 2.4 - Descriptive statistics by brand

Brands	Distance to CBD	Distance to AIR	Price in dollars
Courtyard	5.715	5.253	80.88
Hilton	8.116	8.823	74.82
Hojo	6.906	4.566	45.78
HolidayInn	4.571	4.926	65.45
Hyatt	7.076	3.366	98.46
Marriott	9.922	3.658	95.14
Ramada	2.000	9.693	47.84
Sheraton	9.100	8.007	78.60

4. Results

4.1 <u>Estimation Procedure</u>

We estimate the parameters of the aggregate demand function, explicitly accounting for endogeneity in price and location. This is achieved by employing the contraction mapping procedure of Berry (1994). Among other things, the contraction mapping procedure facilitates use of linear instrumenting techniques to correct for endogeneity. We then estimate the supply side first-order optimization rules for price. We briefly outline the procedure used for estimation. The estimation equates the observed shares to the predicted shares from our model. Note, however an observation is the simulated choice probabilities of an individual for a market (city-year combination). Since the number of properties (consideration set) changes per market, the vector of choice probabilities vary per city. The market shares for each property are obtained by averaging the individual choice probabilities across the simulated individuals for that market. It is these market shares probabilities that serve as the predicted shares for the estimation procedure.

Due to the endogeneity in price and location we implement a procedure similar to Berry (1994) using two nested loops. The inner loop involves computing the individual-invariant parameters of the model, while the outer loop involves computing the individual specific parameters. The actual steps of the estimation are as follows:

Stage 1: Keeping the outer loop parameters fixed (obtained from initial guess), we estimate the inner loop (individual invariant parameters) by minimizing the distance between the predicted shares S_{hm} from the model and observed shares using a non-linear optimization procedure. This step yields estimates for the population level mean utilities for each property as intercepts $\overline{V}_{hm}$ where $\overline{V}_{hm}$ is as below

$$\overline{V}_{hm} = \gamma_j - \alpha p_{hm} - \phi_1 d_{hCBDm} + \phi_2 d^2_{hCBDm} - \phi_3 d_{hAIRm} + \phi_4 d^2_{hAIRm} + \xi_{hm}$$

As motivated in section 2, both price and location measures can be correlated with ξ making the OLS estimator inconsistent for estimating the population level mean parameters $\gamma, \alpha, \phi_1 - \phi_4$. Note however that the recovered $\overline{V}_{hm}$ is linear function of observed and unobserved product attribute (ξ_{hm}). Therefore we use linear instruments based 2SLS estimator to obtain unbiased estimates of $\gamma, \alpha, \phi_1 - \phi_4$.

Stage 2: The market specific ξ's are obtained as residuals of the 2SLS regression from Stage 1.

Stage 3: The error term ξ is then interacted with the instruments used in the Stage 1 to provide the GMM objective function, which is then used for estimating the outer loop (individual specific) parameters.

Stage 4: Iterated over different values for heterogeneity parameters till the GMM objective function from Stage 3 in maximized and the convergence criterion is met[30].

Stage 5: As a test of robustness, we repeat Step 1 though Step 5 for different starting values drawn from a Halton sequence[31].

---

[30] A detailed description of the estimation procedure can be obtained from the authors. A Maximum Likelihood procedure was also implemented. It relied on a normality assumption on the distribution of the ξ, unlike the GMM procedure. Only the GMM results are presented in the paper. MLE results can be obtained from authors. Our GMM based estimation algorithm is akin to Chintagunta (2001) wherein another non-linear demand model i.e. aggregate Probit is estimated.

[31] Like Nevo (2000) we use draws from a multivariate normal distribution to simulate individual's preference for attributes. One limitation of this approach as pointed out by Kim et al. (1995) and Brownstone and Train (2002) is that it allows for both positive and negative individual coefficients for price and location. They suggest draws from an alternative distribution within a restricted range (truncated normal distribution).

We need instrumental variables for the endogenous price and location variables. Like Nevo (2000), controlling for brand specific means, we assume that market specific valuations are independent. We select variables in other markets as instruments for price and location in focal market. We use the following variables as instruments: average annual gas price indices in the focal market; distance from airport and CBD in other markets; annual prices in all other markets. The intuition being that while prices and location might be correlated across markets, the demand shocks are uncorrelated across markets [32]. That is, if $\boldsymbol{\theta}$ is a vector of parameters of the model then

$$\boldsymbol{S}_{hm}(\boldsymbol{\theta}, \xi_{.m}) = \boldsymbol{S}_{hm}^{obs}$$

where $\boldsymbol{S}_{hm}^{obs}$ is the observed market share. Since the demand model is non-linear, as a test of robustness we check whether the estimation procedure converges to the same point with different starting values.

Given the high dimensionality of the parameter space, starting values generated by traditional random sequence generators may have certain limitations (Bhat, 1999; Revelt and Train, 2000). Instead we generate a Halton sequence of draws for starting values. Unlike traditional robustness testing methods where the objective is true randomness to ensure that the same convergence point is reached regardless of starting point, in high dimension search spaces, true randomness might not achieve the objective of efficient and thorough search of the parameter space. The Halton sequence procedure is an alternative process for efficient coverage of the parameter space in such situations. Numerical analyses have found that a smaller number of

---

[32] Bronnenberg and Mahajan (2001) find strong support for spatial dependence between markets that are ``close''. In order to rule out such dependence, we regressed demand shock, from Stage 2 for an alternative, on its own demand shock from other markets. The coefficients on other market demand shocks were statistically insignificant, lending more validity to our choice of instruments. This is not surprising given our seven markets are non-neighboring cities in Texas.

Halton draws is as effective as a larger number of pseudo-random draws using a random number generator (Revelt and Train, 2000).

Exogenous cost indices for electrical utilities and services were obtained only at the market level. We model the effects of these cost drivers as being at the brand-level rather than property level, given the received wisdom in the industry that higher price brands are likely to have variable operating costs.

Since the market shares sum to one, the error terms in the demand equations are correlated. This makes seemingly unrelated regression (SUR) a better estimator than OLS. We use the Hausman (1978) test to test for endogeneity of price and location. Under the null hypothesis that price and location are exogenous, the seemingly unrelated regression (SUR) estimator provides consistent estimates of the demand parameters. On the other hand, 2SLS provides consistent estimates both under the null and alternate hypotheses (Amemiya, 1985). The Hausman test, which basically compares the estimates of SUR and 2SLS estimators, leads to rejection of the null hypothesis ($p<.01$) that prices or location are exogenous.[33] The final step involves estimating the first order conditions for price given by equations (27).

4.2 ***Results***

While several competing models were estimated results for homogenous MNL, mixed MNL, homogenous GNL and mixed GNL are only presented in Table 2.5. We report

[33] Results of OLS, SUR and 2SLS procedures can be obtained from the authors on request.

results for mixed logit as a benchmark given its widespread usage in marketing and economics.[34]

As Table 2.5 indicates, based on sum of squares errors alone mixed GNL outperforms the other two models. Apart from within-sample SSE criteria, the Full Model i.e. Mixed GNL was chosen over other competing demand models (Mixed Logit, Mixed NL) using both the Cox criteria and Encompassing Test criteria for non-nested competing models using GMM as proposed in Smith (1992) [35]. Interested readers can refer to Smith (1992) for a more detailed explanation of the model selection criteria.

These non-nested test criteria evaluate how the alternative models explain the residual unobserved determinants of market share of a chosen null model. The two tests proposed in Smith (1992) are generalizations of Singleton (1985) allowing for non-nested tests for competing regression models estimated using instrumental variables and GMM estimation. Results for exogenous location and price for MNL, Mixed Logit and Mixed GNL can be obtained from the author. We observe a downward bias due to endogeneity in the location parameters, consistent with the findings of Besanko et al. (1998), and Besanko et al. (2003) for price endogeneity.

Not only is the Full Model chosen based on the two non-nested model selection criteria, but also the estimated mean price and mean location parameters for mixed GNL and mixed logit are statistically significantly different from one another.

[34] Similar comparisons have been made between mixed probit and mixed logit using a) panel data (Chintagunta and Honore, 1996) and b) aggregate data (Chintagunta, 2001). This is an important contribution of this paper, since the resulting aggregate elasticities affect market power.

[35] If H_0: E_0[Full Model]=**0** and H_{alt}: E_1[Non-Nested Variant Model]=**0** are the two competing hypothesis then the form of the Cox statistic $\square_t(H_o \mid H_{alt})$ is that of a GMM specification test (Newey, 1985) and is amenable to local power analysis. Similarly the form of the Encompassing test statistic $\mathrm{E}\pounds_t(H_o \mid H_{alt})$ has a limiting chi-squared distribution.

Benchmarking our demand specification i.e. aggregate mixed GNL with the commonly used aggregate mixed logit using aggregate data, is an important contribution of this essay, since the resulting aggregate elasticities affect market power. As our results indicate, misspecification of mixed MNL as the appropriate demand specification for our industry and data would yield an inaccurate picture of market power. The heterogeneous logit and GNL results indicate statistically significant variation in tastes for price and location within the market. The signs and relative magnitudes of the location specific coefficients indicate greater preference for proximity to CBD. The signs of the ϕ_3 and ϕ_4 suggest increasing utility as a property moves further away from AIR.

Note that this does not imply that there is only one ideal point i.e., CBD. Our results indicate 2 ideal points, albeit having very different considerations. The results could be driven by underlying unaccounted segmentation in the market where some consumers have a high preference for properties closer to downtown and away from airport, while another small segment prefers to be closer to airport. The latter segment could be a small captive segment comprising of customers like airline crew, transit passengers who prefer to be closer to airport without much consideration for distance of property from downtown. What we see in our results is the net effect of the two segments[36]. Our intuition is consistent with the data where we see a lot more clustering happening around CBD than airport (685 properties vs. 339 properties). On average consumers are willing to pay \$1.44 to be one mile closer to the central business district, and \$1.22 to be one mile away from the airport.

---

[36] Hence there could be a segment that actually prefers to be closer to airport despite signs on coefficients ϕ_3 and ϕ_4.

Table 2.5 - Estimates of demand parameters

Parameter	Homogenous GNL	Mixed logit	Heterogeneous GNL
Courtyard brand constant	-1.980*	-1.860*	-1.257*
Hilton brand constant	-0.453*	-0.912*	-0.671*
Hojo brand constant	0.613	0.630*	0.511
Holiday Inn brand constant	-1.486*	-0.148	-0.152*
Hyatt brand constant	-1.521*	-1.631*	-1.465*
Marriott brand constant	2.650	1.836*	1.742*
Ramada brand constant	1.880*	2.735*	2.370*
Sheraton brand constant	-2.201*	-0.123	-1.350*
Price : $-\alpha$	4.630*	3.148*	3.211*
Dist. To CBD : $-\varphi_1$	1.689*	4.353*	4.614*
Dist. To CBD^2 : $-\varphi_2$	0.192*	0.591*	0.435*
Dist. To Airport :$-\varphi_3$	-1.835*	-3.610*	-3.906*
Dist. To Airport^2: $-\varphi_4$	-0.116*	-0.192*	-0.129**
Variance in α : σ_α	.	0.841*	0.062*
Variance in φ_1 : $\sigma_{\varphi 1}$	.	0.623*	0.612*
Variance in φ_2 : $\sigma_{\varphi 2}$	.	0.429*	0.456*
Variance in φ_3 : $\sigma_{\varphi 3}$	.	0.906	0.751
Variance in φ_4 : $\sigma_{\varphi 4}$	.	0.441*	0.394*
Courtyand in Nest 1	0.243*		0.287*
Hilton in Nest 1	0.259*		0.164*
Hojo in Nest 1	0.118**		0.101
Holiday Inn in Nest 1	0.312*		0.223
Hyatt in Nest 1	0.221*		0.147
Marriott in Nest 1	0.334		0.345**
Ramada in Nest 1	0.367		0.289**
Sheraton in Nest 1	0.243		0.248*
Courtyand in Nest 2	0.292*		0.384*
Hilton in Nest 2	0.516*		0.552*
Hojo in Nest 2	0.192*		0.281*
Holiday Inn in Nest 2	0.558*		0.603*
Hyatt in Nest 2	0.513*		0.671*
Marriott in Nest 2	0.302		0.243
Ramada in Nest 2	0.161*		0.199*
Sheraton in Nest 2	0.261*		0.209*
Logsum nest 1: μ_1	0.071*		0.118*
Logsum nest 2: μ_2	0.303*		0.443*
Logsum nest 3: μ_3	0.248*		0.313*
Variance in μ_1			.04*
Variance in μ_2			.141*
Variance in μ_3			.095*
Minimized SSE	95.43	99.26	83.43

Consider next the parameters associated with the heterogeneity distribution. A closer examination of the heterogeneity estimates (σ's) for price and location suggests that mixed logit on average overestimates heterogeneity compared to heterogeneous GNL (3 of 5 estimated heterogeneity parameters are much higher for the mixed logit and statistically significant, the other 2 differences in heterogeneity are smaller and not statistically significant). A possible interpretation of this is as follows: what mixed logit classifies as consumer heterogeneity is made of two parts- lower consumer heterogeneity versus higher heterogeneity of purpose of visit and hence different choices for the same consumer. An individual-level demand model would be able to separate these two effects out, but at the aggregate level, mixed logit is unable to, and mixed GNL begins to address the issues. Despite GNL's flexibility, accounting for heterogeneity does increase model fit. The statistically significant heterogeneity estimates for the log-sum parameters provides evidence of error heterogeneity. Failure to account for this as in the case of the heterogeneous logit, results in biasing the taste heterogeneity parameters.

We exogenously specify three nests for both homogenous GNL and mixed GNL[37]. The nest memberships will indicate if nests are driven solely by proximity to ideal points or price alone or by a composite measure of price, location, brand and other omitted product attributes. We treat this composite to capture overall quality of the property (or the overall utility). Let us first examine if nest membership is driven by price alone. Note that in nest 2, the brands with the highest allocation parameters are Hilton (0.55), Holiday Inn (0.60) and Hyatt (0.67). In the full-service sector of hotels, Holiday Inn is classified as a midscale brand, Hilton as upscale and Hyatt as

[37] That is, we have 3 nests for purchase, and one for the outside good. Data constraints prevent a larger number of nests. We report only the 3-nest results; these are statistically superior to the 2-nest results. The search for appropriate nesting structure was conducted over four possible structures – 1) based on industry classification 2) price alone 3) location alone and 4) all alternatives in each nest. We report results for the case 4) where each alternative is available in both nests.

upscale. Therefore, it does not appear as if nest 2 membership composition is based on price alone. Similar observations can be made for nests 1 and 3.

Next, we examine if nest membership is based on location alone. To do this, we calculate the average distance from AIR and CBD for each of the 3 estimated nests. These numbers are reported in Table 2.6. It appears from these numbers that if we were to classify the nests based on distance alone, nest 1 would correspond to AIR, nest 2 to CBD and nest 3 "other", possibly a suburban nest corresponding to an office complex, or tourist destination (e.g., beach), etc. Next, we report the estimated nest shares for the 3 nests. Finally, from the data, we calculate how many properties actually fall within a circle of radius equal to average distance from AIR and CBD foci.

Table 2.6 - Estimated nest shares of properties

	Average price	Average distance to CBD	Average distance to AIR	% Market Share
Nest1	16.840	7.039	2.082	11.73
Nest2	23.827	2.439	7.718	69.99
Nest3	21.224	4.806	6.982	18.28

Market share of properties as a function of distance from foci

Distance from CBD	Distance from AIR
2.5 miles- 40.03%	2 miles = 14.8%
3 miles = 44.9%	4 miles = 15.4%
5 miles = 56.6%	5 miles = 18.9%

Comparing the last two sets of numbers, we find that the nest 1 (AIR) has lower estimated membership (11.73%) than properties located physically close to AIR (14.8%), and nest 2 (CBD) has higher estimated membership (69.99%) than properties physically located close to CBD (40.03%). This means that properties can be further away from downtown (than the average distance in this nest) and still be considered in the CBD choice set by consumers, possibly because they offer lower price or some other unobserved attributes.[38] Similarly, properties that are located physically close to AIR serve demand not directly related to the AIR choices, likely because they compete effectively with properties in nest 3 by offering lower price or some other unobserved attribute like better facilities or transportation etc. Summarizing, while nests are broadly distance based (AIR, CBD and other), the substitution patterns are more complex than simply distance based. In other words, a firm's competitive set is determined not by proximity or quality tiers alone, but by a combination of the two, and other unobserved attributes.

Consider next the estimated logsum parameters. The logsum of the nest with outside good is set to be 1 for identification purposes. These structural nest parameters or logsums are significantly different from one another, suggesting violation of IIA property in the data. They also lie between 0 and 1 and are hence consistent with random utility maximization. Nest 2 or the CBD nest has the highest logsum parameter (0.443) or has the most dissimilar properties of the three nests, nest 1 has the most homogenous membership (0.118). This is not surprising in light of our previous discussion of properties not near CBD being considered as part of the CBD nest.

As discussed in the model section, own and cross-price elasticities in GNL are functions of both the allocation and log-sum parameters. Table 2.7 reports these elasticities for various brands.

---

[38] Recall that consumers have positive utility to being close to CBD. Hence, if a property is located farther away from CBD, it would have to drop price to effectively compete with CBD hotels.

Table 2.7 - Estimated price elasticities

Change in Price	Change in Market Shares							
	Lower priced/ "Midscale"			Medium priced/ "Upscale"		High priced/ "Luxury"		
	Hojo	Holiday Inn	Ramada	Courtyard	Hilton	Hyatt	Marriott	Sheraton
Hojo	-2.938	0.375	0.317	0.111	0.093	0.078	0.302	0.071
Holiday Inn	0.278	-4.333	0.155	0.305	0.087	0.112	0.255	0.048
Ramada	0.332	0.212	-1.288	0.440	0.432	0.239	0.223	0.255
Courtyard	0.162	0.246	0.447	-3.519	0.460	0.178	0.386	0.0322
Hilton	0.122	0.108	0.410	0.328	-6.080	0.604	0.292	0.713
Hyatt	0.054	0.094	0.390	0.211	0.657	-5.202	0.339	0.611
Marriott	0.160	0.168	0.319	0.331	0.232	0.398	-3.452	0.665
Sheraton	0.010	0.043	0.213	0.160	0.624	0.533	0.591	-3.221

Examining own price elasticities, we find some interesting patterns. The highest own-price elasticity is for Hilton (-6.08), which is a medium-priced brand, and the lowest own-price elasticity is for Sheraton, a high-priced brand. So clearly price elasticities are not just functions of the price tiers of firms. Looking at cross-price elasticities, Hilton-Sheraton has the largest cross elasticity while Sheraton-Hojo has the lowest cross elasticity. The price elasticity table reveals some counterintuitive results. Industry classification puts Hilton in the middle (upscale) price tier, and Sheraton is the high price luxury tier. One would expect price elasticities between hotels in the same tier to be higher than those across tiers. Counter to this belief, our results show that the price elasticity between Sheraton and Hilton (0.71) is higher than the elasticity between Sheraton and Marriott (0.66) or Sheraton and Hyatt (0.61) (the differences here are econometrically significant). Note that these price elasticities control for location choices as well and hence are not comparable to industry classifications that are likely based on location-unadjusted pricing.

Therefore, unlike industry classifications that assume that competition is mainly based on price (and hence the price-tier classification), in our data we see firms competing in both price and geographic location. Let us now turn to the supply side estimates[39]. Table 2.8 has the cost estimates. Marginal cost location parameters suggest that marginal cost increases at an increasing rate as a property moves further away from CBD. Therefore, CBD is an ideal point both from demand and cost perspective. These costs of operating further away from CBD can be interpreted as

Table 2.8: Estimates of supply-side parameters

Parameters	Estimates
Courtyard brand intercept	0.457*
Hilton brand intercept	1.439*
Hojo brand intercept	0.321*
Holiday Inn brand intercept	0.416*
Hyatt brand intercept	3.518*
Marriott brand intercept	2.451
Ramada Inn brand intercept	0.330
Sheraton brand intercept	2.615**
Dist. to CBD $\rho 1$	2.463*
Dist. to CBD^2 $\rho 2$	0.063*
Dist. to Airport $\rho 3$	-2.175*
Dist. to Airport^2 $\rho 4$	0.014
Courtyard*elect.utils	2.338
Hilton*elect.utils	2.348**
Hojo*electr.utils	0.158**
HolidayInn*elect.utils	1.761
Hyatt*elec.utils	5.163*
Marriott*electr.utils	3.090*
Ramada*electr.utils	1.863
Sheraton*electr.utils	2.269*
Courtyard*services	2.869**
Hilton*services	3.347*
Hojo*services	0.668*
HolidayInn*services	1.123
Hyatt*services	6.774*
Sheraton*services	3.587*
Marriott*services	4.660**
Ramada*services	1.817*

[39] We present the supply side results only for the heterogenous GNL model. Interested readers can contact the authors for supply side results for MNL, Mixed MNL and NL models.

the extra cost of competing with properties closer to CBD, and could include higher a variety of things e.g., having to offer shuttle services to downtown, offering other attractive features relative to CBD hotels, etc. Given the clustering of properties near CBD, the result of costs increasing as a property moves away from CBD could also be interpreted as there being cost benefits to agglomeration near CBD. For example, it might be easier for agglomerated properties to have shared shuttle services from CBD to the airport or tourist attractions, or cheaper for suppliers to drop off supplies to several agglomerated properties.

Marginal cost increases at a decreasing rate as the property moves further away from AIR. This can be explained in at least two ways: first, if being closer to AIR is not attractive for a large segment of the population, then clearly being away from AIR means fewer costs have to be incurred to attract consumers (i.e., the reverse of the argument above for properties not close to CBD). Second, again similar to the argument above, it is possible that costs of suppliers are lower for properties further away from AIR, or that city taxes (other than on prices which have been accounted for in the data) or other variables costs are higher near AIR.

Several of the brand specific intercepts in the marginal cost function are statistically significant. The parameters for the exogenous cost shifters take higher values for luxury brands than non-luxury brands. The overall cost for a luxury brand is higher than for non-luxury brands, as reported in Table 2.9. That is, the correlation between price and estimated marginal cost is very high (.90). As an ex-post check of our marginal cost specification, we also calculated the correlation between estimated marginal costs and number of properties per brand per city. This correlation is very low (.001), ruling out economies of scope. The correlation between capacity and marginal costs is .48, and capacity and prices is .53. This can be interpreted as market power of larger hotels.

Table 2.9 - Brand-level supply side descriptors

Brand	Estimated marginal cost	Dollar price	Properties/market	Capacity/property
Courtyard	32.3	80.88	2.17	145
Hilton	36.2	74.82	1.43	292
Hojo	19.3	45.78	1.02	161
HolidayInn	27.9	65.45	3.77	217
Hyatt	42.2	98.46	1.83	369
Marriott	38.3	95.14	2.5	430
Sheraton	28.8	47.84	3.02	175
Ramada	32.9	78.60	1.25	676

To summarize our results from this exercise, our results indicate that location, like price, matters both on the demand and cost side. We demonstrated the gains of GNL in explaining this market over the more commonly used mixed logit. Note especially the lower heterogeneity estimates of GNL, possibly due to the more flexible substitution patterns allowed by the model (e.g., allowing for taste and error heterogeneity in choices of any given consumer reduces the estimate of heterogeneity across consumers). The allocation parameters indicate that nest membership is not simply a function of price or location, but a combination of that and other unobserved factors.

5. Conclusion

In this essay, we study the significance of price and geographic location as important elements of a firm's product marketing mix. In our industry and data context, choice heuristics are not obvious, and there is missing information on several attributes likely to matter to consumer choice. Therefore, we argue that the

GNL is a good consumer choice model and its results will be a more accurate input in to determining firms' competitive pricing choices.

We find location attributes of retail properties affect both consumer demand and firm costs. We also find strong evidence to support the role of location as a source of market power (through lower costs and through the ability to charge higher prices). This essay thus provides a compelling argument for, and empirical validation of, the location-price link for differentiated oligopolies. Therefore, firms compete with not just their immediate same-price neighbors but also with lower-price distant neighbors, and these location-adjusted price elasticities are equally important in determining with whom firms compete.

The contributions of the essay are both methodological and substantive. Methodologically, we demonstrate for our industry and dataset, GNL based demand model that also accounts for taste and error heterogeneity, offers distinct benefits and statistical superiority over the popular mixed logit. Its ability to accommodate flexible patterns of substitution between choices results in more accurate predictions of the price and location response parameters, and a more accurate picture of the competitive landscape. Substantively, we capture the competitive effects of a price and location choices. Additionally, we account for the price-location links on both the demand (via multiple ideal points) and supply side (econometrically controlling for endogeneity of price and location, and costs of firms as a function of location).

The methodology employed in this essay can be used to test for price-location interactions in other retail environments where price and location are strategic variables. The flexibility of substitution patterns offered by GNL makes is a good alternative for situations in which nesting structures are not obvious and when unobserved attributes might be especially important in these nesting structures. An example of such an application is models of store-brand choices for studying retail competition, or for studying car choices where a number of alternative nesting structures are possible.

To enrich our understanding of the consumer decision making in these situations, it would be useful to complement market-level data with individual-level choice data (Berry et al. (2004) and Chintagunta and Dube (2003)), unlike the present essay that relies only on aggregate data. Another extension would be to use the GNL framework to not just characterize the final choice but also the antecedent consideration set formation (Swait 2000). We look forward to future work in this area.

REFERENCES

Amemiya, T., 1985. *Advanced Econometrics*. Cambridge, MA: Harvard University Press.

Anderson, S.P. and dePalma, A., 1992. Multiproduct firms: a nested logit approach. *Journal of Industrial Economics* 40, pp. 261-276.

Baum, Joel A.C., and Heather A. Haveman, 1997. Love thy neighbor? Differentiation and spatial agglomeration in the Manhattan hotel industry. *Administrative Science Quarterly,* 42: 304-338.

Bhat, C.R., 1999. Quasi-Random Maximum Simulated Likelihood Estimation of the Mixed Multinomial Logit Model. *Working paper,* University of Texas, Austin.

Besanko, David, Sachin Gupta, and Dipak C. Jain, 1998. Logit Demand Estimation Under Competitive Pricing Behavior: An Equilibrium Framework, *Management Science*, 44 (11), 1533-47.

Berry, Steve, 1994. Estimating Discrete-Choice Models of Product Differentiation. *RAND Journal of Economics*, Vol. 25 (2) pp. 242-262.

Berry, Steve, James Levinsohn and Ariel Pakes, 1995. Automobile Prices in Market Equilibrium. *Econometrica*, 841-890 Vol. 63 (4) pp. 841-890.

Berry, Steve, James Levinsohn and Ariel Pakes, 2004. Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market. *Journal of Political Economy*, (Forthcoming).

Bodapati, A. and S. Gupta, 2004. The Recoverability of Segmentation Structure from Store- Level Aggregate Data. *Journal of Marketing Research* (Forthcoming).

Börch-Supan, A. and V.A. Hajivassiliou, 1993. Smooth Unbiased Multivariate Probability Simulators for Maximum Likelihood Estimation of Limited

Dependent Variable Models. *Journal of Econometrics*, Vol. 58, No. 3, pp.347-368.

Bresnahan, Timoth, S.Stern and M.Trajtenberg 1997, Market Segmentation and the Source of Rents From Innovation: Personal Computers in the Late 1980s, *Rand Journal of Economics* 28(0), 17-44.

Bronnenberg, Bart J. and Vijay Mahajan, 2001. Unobserved Retailer Behavior in 0 Multimarket Data: Joint Spatial Dependence in Market Shares and Promotion Variables. *Marketing Science*, 20:3 (Summer), 284-299

Chintagunta, Pradeep K., 1993. Investigating Purchase Incidence, Brand Choice and Purchase Quantity Decisions of Households. *Marketing Science*, 12, 184-208.

Chintagunta, Pradeep K., 2001. Endogeneity and Heterogeneity in a Probit Demand Model: Estimation Using Aggregate Data. *Marketing Science*, 20, 4, 442-456

Chintagunta, Pradeep K., and Dube, J. P., 2003. Estimating an SKU-level Brand Choice Model Combining Household Panel Data and Store Data. *Working Paper*.

Choi, S. C., W. S. DeSarbo and P. T. Harker, 1990. Product Positioning under Price Competition. *Management Science*, 36, pp. 175-199.

-------,1992. A Numerical Approach to Deriving Long-Run Equilibrium Solutions in Spatial Positioning Models. *Management Science*, 38, 1, pp. 75-86.

Cotterill, Ronald W, 1986. Market Power in the Retail Food Industry: Evidence from Vermont. The *Review of Economics & Statistics*, 379-86 Vol. 68 (3) pp. 379-86.

Davis, Peter, 2002. Entry, Cannibalization and Bankruptcy in the U.S. Motion Picture Exhibition Market, *Mimeo* MIT.

Daganzo, C. *Multinomial Probit: The Theory and its Application to Demand*

Forecasting. Academic Press, New York, 1979.

Guadagni, Peter and John D.C. Little , 1983, A Logit Model of Brand Choice Calibrated on Scanner Data, *Marketing Science*, 2 (Summer), 203-38.

Haining, R. P., 1984. Testing a spatial interacting-markets hypothesis. *Review of Economics and Statistics,* 66, 576-583.

Hajivassiliou, V. H., and D. McFadden, 1990, The Method of Simulated Scores for the Estimation of LDV Models with an Application to External Debt Crises, *Cowles Foundation Discussion Paper* 967, Yale University.

Hannan, Michael T. and Freeman, John, 1977, The Population Ecology of Organizations, *American Journal of Sociology.*

Hauser, John R., 1988. Competitive Price and Positioning Strategies, *Marketing Science*, vol. 7, No. 1, (Winter), 76-91.

Hauser, John R., and Steven M. Shugan, 1983. Defensive Marketing Strategy. *Marketing Science*, Vol. 2, No. 4,(Fall), 319-360.

Hausman, Jerry A, 1978. Specification Tests in Econometrics. *Econometrica*, Vol. 46 (6) pp. 1251-71.

Huff, L.D (1966), Programmed Solution for Approximating an Optimum Retail Location, *Land Economics*, 42 (3): 293-303 1966

Hotelling, H., 1929. Stability in Competition. *Economic Journal* 39, pp. 41-57.

Johnson, Ronald N. and Parkman, Allen M., 1983. Spatial Competition and Vertical Integration; Cement and Concrete Revisited: Comment/Reply The *American Economic Review*.

Johnson, N.L. and S. Kotz, 1970. *Distributions in Statistics: Continous Multivariate Distributions*. Chapter 21, John Wiley, New York.

Kamakura, Wagner and Gary J. Russell, 1989. A Probabilistic Choice Model for Market Segmentation and Elasticity Structure. *Journal of Marketing Research*, 26, pp. 379-90.

Kamakura, Wagner, Kim Byung-Do, and Jonathan Lee, 1996. Modeling Preference and Structural Heterogeneity in Consumer Choice. *Marketing Science*, Vol. 15 (2)

Kamita, Rene, 2001. Merger Analysis in Geographically Differentiated Industries With Municipal and Private Competitors: The Case of Solid Waste Disposal. *Mimeo* UC Berkeley.

Kannan, P. K. and Gordon P. Wright, 1991. On Testing Competitive Market Structures. *Marketing Science*, Vol. 10, No. 4, pp. 338 - 34.

Keane, M. A., 1994. Computational Practical Simulation Estimator for Panel Data. *Econometrica*, Vol.62, No.1, pp.95-116.

Krishnamurthi, Lakshman and S.P. Raj, 1991, An Empirical Analysis of the Relationship Between Brand Loyalty and Consumer Price Elasticity. *Marketing Science*, 10, Spring, 172-183.

McFadden, D., 1973. Conditional Logit Analysis of Quantitative Choice Behavior, in Zaremmbka P. (ed.), *Frontier of Econometrics*, Academic Press, New York.

McFadden, D., 1989. A Method of Simulated Moments for Estimation of Discrete Choice Response Models without Numerical Integration. *Econometrica*, Vol.57, No.5, pp.995 1026.

McFadden D., 1978. Modeling the Choice of Residential Location, *Transportation Research Record*, No. 672, pp. 72-77.

Nevo, A., 2001. Measuring Market Power in the Ready-to-Eat Cereal Industry. *Econometric*a, 69(2), 307-342.

Nevo, A., 2000. A Practitioners Guide to Random Coefficients Logit Models of Demand. *Journal of Economics and Management Strategy*. 9(4).

Newey, W.K., 1985. Generalized Method of Moments Specification Testing. *Journal of Econometrics*, 29, 229-256.

Newey, W.K. and D.L. McFadden, 1994. Large Sample Estimation and Hypothesis Testing, in: R.Engle and D.L.McFadden, eds., *Handbook of Econometrics*, Vol.4, Amsterdam:North- Holland.

Revelt, D., and K. Train, 2000. Customer Specific Taste Parameters and Mixed Logit Models. *Working Paper*, University of California, Berkeley.

Singleton, K.J., 1985. Testing Specifications of Economic Agents' Intertemporal Optimum Problems in the Presence of Alternative Models. *Journal of Econometrics*, 30, 391-413.

Seim, Katja, 2000.Geographic Differentiation and Market Structure: The Video Retail Industry, *mimeo* Stanford University.

Smith, Richard J., 1992. Non-Nested Tests for Competing Models Estimated by Generalized Method of Moments. *Econometrica*, Vol. 60, No. 4, 973-980.

Sudhir, K., 2001. Competitive Pricing Behavior in the Auto Market: A Structural Analysis, *Marketing Science*, 20 (1),42-60.

Swait, J., (2000). Choice Set Generation Within the Generalized Extreme Value Family of Discrete Choice Models, *Transportation Research Part B* .

Swait, Joffre, and Adriana Bernardino. 2000. Distinguishing taste variation from error structure in discrete choice data. *Transportation Res. Part B* 34(1) 1 – 15.

Thomadsen, R., 1999. Price Competition in Industries with Geographic Differentiation: The Case of Fast Food, *Mimeo*, Stanford University, Stanford, CA.

Train, E. Kenneth, 2003. Discrete Choice Models with Simulation. *Cambridge University Press.*

Villas-Boas, M, and Zhao, Ying, 2003. The Ketchup Marketplace: Retailer, Manufacturers, and Individual Consumers. *Working Paper*.

Vovsha, P., 1997. The cross-nested logit model: Application to mode choice in Tel

Aviv metropolitan area, Conference presentation, 76th Transportation Research board meetings, Washington, DC.

Wen, C.H. and Koppelman, F.S., 2001. The Generalized Nested Logit Model. Transportation Research-B, V 35, N 7, pp 627-641.

Wall, G, Dudycha, D and Hutchinson, J., 1985. Point pattern analyses of accommodation in Toronto, *Annals of Tourism Research*, 12(4) pp. 603-618.

ESSAY 3

DYNAMIC EQUILIBRIUM MODEL OF FIRM ENTRY, STAY AND EXIT DECISIONS

Abstract

This paper proposes an empirical dynamic oligopoly model of endogenous market entry, stay and exit decisions. In the lodging industry, decisions of entry and/or exit involve considerable irreversible investment in capital and uncertainty about demand, cost and competition. An inactive firm anticipating better market conditions in the future may differ entry to future periods and in the process risk forfeiting advantages from early entry to its competitors. An incumbent firm in anticipation of future entries or exits, can chose to either continue to stay or exit the market. Hence current and anticipated future market conditions can affect a lodging property's market entry/exit timing decisions.

Despite these long-run considerations, the extant literature predominately uses static/two period models and identifies factors like -- market uncertainty, excess capacity, firm heterogeneity and learning-by-doing -- to affect and in turn be affected by firm entry/exit decisions. Building on prior findings, this paper presents a unified empirical framework accounting for these effects in the context of discrete dynamic games, wherein the firm decisions i.e. entry, stay and exit are endogenously determined in Markov perfect equilibrium. Unlike previous static/two period models, firms in this paper are forward-looking, and maximize their profits over an infinite-time horizon. The optimality conditions are computed numerically using dynamic programming techniques and the model is calibrated using aggregate monthly panel data for the Texas lodging industry from 1991-2003.

1. Introduction

Understanding the antecedents of market structure and the evolution of market structure are central issues in industrial organization. This literature can be broadly classified into descriptive and structural studies (Reiss and Wolak, 2002). Descriptive studies have a very rich history in economics and marketing for example Bresnahan and Reiss, (1990, 1991), Jacobson (1988), Jacobson and Aaker (1985) and Szymanski, Bharadwaj and Varadarajan (1993). A vast majority of these studies use the structure-conduct-performance (SCP) paradigm to provide valuable descriptive insights on the role of production efficiencies and marketing effort on firm/industry performance and market structure (Dasgupta and Stiglitz, 1980; Shaked and Sutton, 1983). Chandler (1990) and Lieberman and Montgomery (1998) address how these factors contribute to first-mover advantage and market structure.

While these studies recognize patterns between economic variables in data, they do not specify an economic model that generates these variables (Kadiyali et al. 2001). Variables like price, costs, concentration that are outcomes of supply and demand side decisions are assumed exogenous in these studies.

The emerging stream of structural models on the other hand focuses on, a single industry (intra-industry) with the objective of exploring how differences among firms in the same industry lead to differences in firm performance. By imposing an economic model grounded in economic theory, the observed data is used to recover the parameters of the economic primitives. Since the underlying economic model is invariant to shocks in the environment the agents operate in, this stream of research lends itself well to "what if" analysis, where outcomes to changes in the economic are simulated (Reiss and Wolak, 2002).

While both these streams of research have made enormous contributions to understanding industrial organization and compliment each other, they share one very significant limitation as explained below.

Across the two streams, accumulated capacity (Saloner, 1987; Ghemawat, 1984), learning-by-doing/experience (Spence, 1981), first-mover advantage (Lieberman and Montgomery, 1994) result in asymmetric differences in industry/firm profits. These studies find that across a majority of industries, production experience and cumulative production causes reduction in per-unit costs (Dutton and Thomas, 1984). This is often referred to in the literature as "learning-by-doing" or "experience" effect. Hence "learning by doing" can be to be a source of increasing returns and consequent first-mover advantages (Spence, 1981; Fudenberg and Tirole, 1983).

While these studies are very helpful in shedding light on the moderating role of accumulated capacity and experience/learning-by-doing on firm profits, they do not model the *process* that led to differences in capacity accumulation, learning-by-doing and first-mover-advantage across firms/industries in the first place[40].

Besanko and Doraszelski (2004) introduce a dynamic equilibrium model that endogenizes and simulates the evolution of capacity accumulation but not cost efficiencies due to learning-by-doing. Benkard (2004) tries to understand the role of learning-by-doing on costs and thereby on the long-run entry-exit decisions of firms in the wide-bodied aircrafts market without studying capacity accumulation.

---

[40] Two exceptions are the Besanko and Doraszelski (2004) and Benkard (2004) studies.

Like the Besanko and Doraszelski (2004) and Benkard (2004) studies, the current paper contributes to the literature by building a long-run equilibrium model where firms accumulate capacity and experience in a market, via endogenous entry, stay and exit decisions. By doing so we model the *process* that led to differences in capacity accumulation, learning-by-doing and first-mover-advantage a limitation of the extant literature. While there might be other contributing factors to differences among firms, like Besanko and Doraszelski (2004) and Benkard (2004) studies, this study limits the analysis to differences generated by the process of market entry, stay and exit decisions alone.

In our model, entry results in capacity accumulation, while staying leads to learning-by-doing advantages either through better understanding of demand or better management of costs. Unlike Besanko and Doraszelski (2004) and Benkard (2004) studies, we *jointly* model *both* the process of capacity accumulation and learning-by-doing advantages, a limitation of these two studies.

The proposed model allows one to probe the sources of the relationship between experience and marginal cost by analyzing the *process* of cost reduction in the lodging industry. Our empirical model allows us to explore how costs vary across brands/firms and over time as a result of experience. Since we model the process of accumulation of capacity in a market by brand, we can assess if geographic agglomeration/clustering by a brand results in softening competition with other properties of same brand and deters future entry of its competitors (properties belonging to other brands).

Our proposed model accommodates strategic firm behavior. This is achieved through the optimality conditions, which in our case do not bound lodging properties to stay out of the market if current period profits are non-positive, a limitation of traditional static models. Thus our model allows firms to enter early either to reap benefits a) from "learning-by-doing" cost efficiency or b) from geographic agglomeration or to c) deter future entry. The model has a number of distinctive implications regarding market concentration, capacity accumulation and learning that are empirically tested.

We exploit a rich new data set to analyze the role "learning-by-doing" and capital accumulation on the evolution of market structure of the lodging industry. Our analysis, finds strong empirical support for "learning-by-doing" cost efficiency. Cumulative experience of a lodging property (within a geographic market) reduces marginal cost but does so at a decreasing rate. We find that managers of lodging properties with "learning" cost advantage exploit their advantage to deter future entry of competitors. Counter to previous findings we find that "capacity accumulation" does not deter future entry of properties of the same brand and hurts long-run profits.

The paper is organized as follows. Section 2 reviews the literatures on entry/exit and competitive dynamics. Section 3 describes the -- lodging industry -- the focal industry for our empirical analysis. Section 4 introduces the data used to calibrate the proposed model. Section 5 details our empirical model. Sections 6 and 7 provide details on the estimation procedure and results. Section 8 summarizes our findings and proposes directions for future research.

2. Literature Review

This study makes both methodological and substantive contributions to the literature on entry-exit and competitive dynamics. We review the two literatures in this section and provide explanation of the contributions made by this paper to both these literatures.

*2.1 **<u>Entry/Exit Literature Review</u>***

Modeling the market entry/exit decisions is not new to marketing or economics. The Prescott and Visscher (1977), Mankiw and Whinston (1986) studies in economics, and Eliashberg and Chatterjee (1985) and Eliashberg and Jeuland (1986) studies in marketing propose analytical models for entry-exit decisions. The Bresnahan and Reiss (1990, 1991) and Berry (1992) studies on the other hand pioneered estimation of equilibrium models of entry/exit studies. Bresnahan and Reiss (1990, 1991) infer competitive interactions between auto dealers from the measures of market size and industry concentration while Berry (1992) models firm entry decisions in the airline industry by modeling firm-specific sources of profit accounting for firm heterogeneity.

Some studies examine other factors that affect entry-exit decisions in a competitive framework include – entry deterrence (Kadiyali, 1996; Ellison and Ellison, 2000), spatial entry models (Mazzeo 2002; Seim 2003), free entry and social efficiency (Berry and Waldfogel, 1999), entry of generic drugs (Scott Morton, 1999) etc. In markets with large setup costs and irreversible investment, factors like demand and cost uncertainty (Dixit and Pindyck, 1994), incomplete and/or asymmetric information (Greenwald and Stiglitz, 1990), early mover advantage (Lieberman and Montgomery, 1994), learning-by-doing cost efficiencies etc., affect long-run entry-exit decisions (Jovanovic and MacDonald, 1994; Sutton, 1991).

In all the studies mentioned above, the focal industries (airlines, pharmaceuticals, photo film, technology markets etc.) firms need to incur substantial costs to enter. Before firms incur these expenses they and their supporting financial institutions assess the long-term survival and financial viability of such investments be it purchasing more planes, setting up a new plant to manufacturer new photo-film or new drug. However despite these long-run considerations, the forementioned empirical studies either use static or two-period modeling framework to model firm entry/exit decisions. These modeling approaches ignore dynamic considerations beyond current/two periods.

While the static/two period approach[41] offers the convenience of tractability, it suffers from the drawback that the final period behaves like a static (one-period) model. However firms expecting continued dynamic behavior in the future may behave very differently than firms anticipating static conditions in future periods as is the case with two-period models.

The contributions of this study to the entry/exit literature are as follows. First, we relax the limitations of static/two period models and examine long-run dynamic considerations that affect firm's decisions to enter, continue or exit a geographic market. Second, making the assumption of forward-looking firms, the proposed model endogenizes long-run competitive entry, stay and exit decisions. Third, these decisions are outcomes of a dynamic game of incomplete information. Incomplete information stems from private shocks to firm costs (cost of entry, per-period maintenance cost and exit cost). The infinite-horizon nature of the model avoids the

[41] Exceptions include Ericson and Pakes (1995), Pakes and McGuire (1994, 2001), Gowrisankaran and Town (1997), Benkard (2004) and Dube' et al. (2003).

final period static problem of the two period models as stated above. Much like the Hopenhayn (1992) and Pakes and Ericsson (1998) studies we study firm dynamics assuming firm and market specific sources of uncertainty.

Four, we account for factors like firm heterogeneity, excess capacity, learning by doing etc. that have been shown to affect firm decisions. These factors can also be affected by firm decisions. The feedback nature of these affects are appropriately captured in the proposed model as a first order Markov process where the evolution of future states is affected by past period market conditions and firm decisions, and influence firm decisions in future states. While some of the factors captured in our model have been studied separately or in part, to the best of our knowledge this study is the first to present a unified econometric framework -- jointly modeling the interdependencies between these factors and firm decisions.

2.2 Competitive Dynamics – Literature Review

Understanding and responding to industry dynamics is an important element of competitive marketing strategy and is not new to marketing. Dolan and Jeuland (1981), , Rao and Bass (1985) and Eliashberg and Jeuland (1986) study pricing dynamics while Kadiyali et al. (1999) and Dube' et al. (2003) study price and advertising dynamics in an oligopoly setting. In economics much of the literature has focused on factors like price (Bain, 1956; Kamien and Schwartz, 1971), experience/reputation (Smiley and David, 1983; Milgrom and Roberts, 1982), capacity (Spence, 1977; Dixit, 1980), learning by doing etc. that affect entry/exit decisions. Seminal papers like Bresnahan and Reiss (1990, 1991), Berry (1992) and more recently studies like Davis (2002), Mazzeo (2002), Seim (2003), Tamer

(2003), Hitsch (2003) and Benkard (2004) propose empirical frameworks to capture some of the effects listed above.

However as stated earlier in this section, with the exception of very few studies, most of the empirical work in economics and marketing examining entry/exit decisions ignore long-run dynamics. Two well-documented econometric issues may have limited the scope of application of more realistic long-run dynamic equilibrium models and its application to study firm entry/exit decisions. First, the *curse of dimensionality* where the costs of equilibrium computation increases exponentially with the number of firms. Second, the *indeterminacy problem* associated with the existence of multiple equilibria (Aguirregabiria and Mira, 2002b).

Recent developments in econometric methods have resulted in introducing novel approaches to estimate structural parameters of empirical dynamic multi-agent games, while reducing the forementioned computation and multiple equilibria problems. Drawing on Rust (1997), Ericson and Pakes (1995) and Pakes and Ericson (1998), Aguirregabiria and Mira (2002a,2002b) and Benkard (2004) propose new estimators to identify structural parameters of multi-agent long-run dynamic games. Dube et al. (2003) and Hitsch (2003) build on techniques proposed in the above studies to model advertising dynamics and firm learning under demand uncertainty.

This essay is similar in spirit to the long-run dynamic empirical studies mentioned above in that it too relies on numerical dynamic programming computational techniques to model equilibrium outcomes, however differs both in methodological and substantive focus. Methodologically, we build on the nested pseudo likelihood algorithm in Aguirregabiria and Mira (2002b). While the Aguirregabiria and Mira (2002b) study is a single agent dynamic equilibrium model, this study proposes a similar nested pseudo likelihood algorithm for an oligopoly market. Rather than looking at continuous dynamic controls like price or advertising e.g. Dube et al. (2003) and Chan et al. (2003), we estimate a long-run discrete control dynamic game of entry, exit and stay decisions.

The proposed model set in an equilibrium framework, allows for a better interpretation of the structural parameters (Reiss and Wolak, 2002; Kadiyali et al., 1999) than reduced form single/two-period models. The model and estimation technique proposed in this essay, add to the growing set of tools in the analysis of empirical dynamic games. The framework can be used to study other important marketing problems like dynamic pricing, sequential release of new products, dynamic aspects of product positioning, product line design, location choice of retail outlets etc.

To summarize, drawing on work in empirical industrial organization we present a Markov perfect equilibrium model to capture the long-run competitive dynamics in firm decisions. We employ a two-step estimation algorithm to estimate the parameters of our long-run dynamic game. We account for observed and unobserved firm heterogeneity thereby guaranteeing existence of a pure strategy Markov perfect equilibria (Doraszelski and Satterthwaite, 2003) while our estimation procedure ensures uniqueness Aguirregabiria and Mira (2002a, 2002b). Our model and findings provide guidance to managers on the effect of the 'option value' of delaying/expediting entry and exit decisions on both long-run cost and revenues. Third, unlike previous reduced form studies on the lodging industry like

Conlin and Kadiyali (2000), we structurally model the role of excess capacity and market uncertainty on entry deterrence[42].

We describe the lodging industry, data, our econometric model and estimator in sections 3, 4, 5 and 6 respectively. The results of the analysis are presented in section 7. Conclusions and directions for future research are presented in Section 8.

3. The Lodging Market

The lodging industry revenue is a significant portion of consumer retail sales. The 2004 Standard and Poor's (henceforth S&P) Lodging and Gaming Industry survey projects annual revenues at about $100 billion from room night sales alone. After accounting for costs of capital, service costs and costs of operation this amounts to about $16 billion dollars in profit. The S&P report states that by mid 2004, national level room-night sales amounted to 2.8 million rooms across 55,000 properties. Adjusting for size of properties this means that the nation wide demand is approximately one hotel room night for every 65 US residents. Unlike traditional consumer packaged goods, demand for hotel rooms comes from both domestic travelers (US residents who reside outside the geographic market in which the hotel is located) and international travelers[43].

While offering "refuge for rest and privacy" via rooms for rent, is viewed as being the primary purpose of the lodging industry, increasing competition has forced

[42] We do not however endogenize capacity decisions.

[43] The number of international visitors to the United States declined 4%, to 40.4 million, in 2003, following a 7% drop, to 41.9 million, in 2002. 30% of international arrivals came from Canada and about 24% from Mexico. (Source - US Department of Commerce's Office of Travel and Tourism Industries)

property managers to differentiate themselves from their competitors by offering features and services like spas, conference centers, pools, gyms and varying degrees of in-room service and amenities[44].

So as to operate and differentiate themselves from their competitors, lodging firms incur significant and irreversible setup costs. Industry experts project these costs as being in the range of a few million dollars per property, with annual nationwide expenditure on new construction being approximately $10.5 billion for year 2004[45]. Tables 3.1 and 3.2 show the distribution of US lodging properties across parent brands and over time. In 2003 alone, 598 new hotels, with 71,691 rooms were opened, a net supply addition of 1.3% (after accounting for closings) over supply in 2002. An estimated 62,984 rooms i.e. a 1.2% rise in net supply, are expected to debut in 2004[46].

These numbers and Tables 3.1 and 3.2 suggest significant cross-sectional and inter-temporal variance in entry, exit and stay decisions among brands. Such investments are usually backed by large lending/commercial banking firms. So firm entry/exit decisions as well consumer demand can also be affected by macro-economic variables. An interesting question to ask is if firms engage in strategic behavior to deter future entry, even after we control for these macro-economic factors? If so does early entry and capacity accumulation provide costs and profit advantages thereby acting as credible threats for future entry? These are some of the questions we attempt to address in this paper. Next we explain the data used for our empirical analysis.

---

[44] Source – Standard and Poor, Industry Report – Lodging & Gaming, August 5, 2004 by Tom Graves, CFA
Casino & Hotel Analyst
[45] Source - US Department of Commerce.
[46] Source - Lodging Econometrics, a research division of National Hotel Realty.

4. Data

For our empirical analysis we assemble a unique database containing information on the lodging properties in several metropolitan markets in Texas. The Texas State Comptroller requires every lodging property to report taxable and non-taxable revenues on a quarterly basis. Source Strategies Incorporated (SSI), an independent marketing research firm located in San Antonio, aggregates and augments this (public) information in their annual reports titled Texas Hotel Performance Factbook. The data contain information on all lodging properties (i.e., hotels, motels, bed-and-breakfasts) in Texas with annual revenues over 13,000 dollars from 1991 through 2003.

Hotel brands are categorized into sectors (Full-Service, Limited-Service or Extended Stay) and segments (Deluxe, Luxury, Upscale, and Midscale with Food and Beverage, Midscale without Food and Beverage, Economy, Budget, Upper-tier Extended Stay and Lower-tier Extended Stay). For the empirical analysis we use data from twelve large geographic markets in Texas. A market is defined as a city-month combination, which results in 12(metros)*13 (years)*12 (months) = 1872 markets.

Since computational load in long-run dynamic equilibrium models increase exponentially with number of firms, we choose to limit the empirical analysis to a single service sector namely -- Midscale [47]. In order to account for sufficient differentiation we selected properties belonging to five large market share brands across different sub-tiers in the Midscale sector. The final sample consists of 1113 unique properties across all markets. Out of these 507 properties entered prior to the

[47] This sector exhibits maximum number of entries and exit relative to Full service and Extended stay sector.

start of our data, 606 entered within the time period of our data. 1027 properties are still in operation, of which 565 entered in our data, leaving 41 properties that entered and exited in our data. We conduct the analysis for the Midscale segment while accounting for market specific variables that capture information on market evolution across the two other segments.

Table 3.3 contains descriptive statistics for the final estimation sample. Note the significant variation in the number of active properties, implying large number of entries and exits. Figures 3.1 and 3.2 provide a clearer illustration of these activities. Figure 3.1 is a graphic showing the number of entries and exits across all markets. However we must also ensure that there is variation within each market. Figure 3.2 provides metro specific entry and exit time series for two such markets[48]. The graphed time-series shows significant variation within each metro. There is also no systematic pattern in entry-exit decisions across markets, therefore for the purpose of the empirical analysis we view these as independent markets i.e. non-competing markets. Combining Figures 3.1 and 3.2, our data demonstrate significant entry/exit dynamics.

Apart from entry-exit information, the data contain aggregate monthly information at the individual property level like brand affiliation, capacity, total rooms nights sold, average-daily-rate (ADR) prices/room-night etc. ADR[49] is estimated from surveys conducted by SSI, financial reports and information from appraisers, chain and AAA directories, and information provided by Smith Travel Resource.

[48] Similar variance is also observed in the other ten geographic markets.
[49] The ADR is the pre-sales tax price.

TABLE 3.1 – Distribution Of Properties And Rooms Across Brands

LARGE HOTEL COMPANIES

(Based on number of affiliated rooms worldwide)

COMPANY	MAJOR CHAINS	NO.OF PROPERTIES*	NO. OF ROOMS*
Cendant Corp.	Days Inn, Ramada (US), Super 8, Howard Johnson, Travelodge (N. Amer.)	6,399	518,435
InterContinental Hotels Group**	Holiday Inn, Inter-Continental	3,500	538,000
Marriott International †	Marriott, Courtyard Residence Inn, Fairfield Inn, Renaissance, Ramada (outside N. Amer.)	2,753	496,920
Accor SA	Motel 6, Mercure, Ibis, Novotel, Red Roof Inns, Hotel Sofitel, Formule 1	3,950	455,000
Choice Hotels Int'l	Comfort Inn, Quality Inn, Econo Lodge	4,678	375,859
Hilton Hotels §	Hilton (US), Hampton Inns, Doubletree, Embassy Suites, Homewood Suites	2,157	345,141
Best Western Int'l ‡	Best Western	4,105	312,329
Starwood Hotels & Resorts	Sheraton, Westin	736	227,815
Carlson Hospitality Group	Radisson, Country Inns & Suites By Carlson, Regent International Hotels	885	147,000
Hyatt Corp.	Hyatt Regency	121	59,000
Total		29,494	3,498,423

*Based on latest data available as of May 2004. **Formerly Six Continents Hotels. †Includes vacation ownership properties and Marriott Executive Residences. ‡Not-for-profit association. §Includes some hotels that are part of other chains.
Sources: Company reports; American Hotel & Motel Association's *2002 Directory of Hotel & Motel Companies*; *Hotel & Motel Management* magazine; Standard & Poor's estimates.

Source – Standard and Poor's Industry Surveys, Lodging and Gaming, August 2004.

TABLE 3.2 – Distribution of Supply, Demand, Occupancy Rates and Revenues Over Time

LODGING FUNDAMENTALS
(Selected performance measures)

YEAR	ROOM SUPPLY (YEAR-TO-YEAR % CHANGE)	ROOM DEMAND (YEAR-TO-YEAR % CHANGE)	OCCUPANCY RATE (%)	AVERAGE DAILY ROOM RATE ($)	AVERAGE DAILY ROOM RATE % CHANGE	REVENUE PER AVAILABLE ROOM ($)	REVENUE PER AVAILABLE ROOM % CHANGE	GROSS OPERATING INDUSTRY REVENUE (BIL. $)	PROFIT AS % OF REVENUES	PRETAX INCOME (BIL. $)
2003	1.2	1.7	59.2	83.12	0.1	49.18	0.6	105.3	35.0	12.8
2002	1.6	0.3	58.9	83.01	(1.4)	48.91	(4.0)	102.6	35.7	14.2
2001	2.4	(3.4)	60.0	84.92	(1.3)	50.96	(5.9)	103.5	37.1	16.2
2000	3.1	3.7	63.5	85.24	4.9	54.15	5.5	112.1	39.1	22.5
1999	4.1	3.0	63.2	81.29	4.0	51.33	2.9	102.9	39.2	22.1
1998	4.2	3.1	63.8	78.17	4.6	49.86	3.6	93.1	40.2	20.9
1997	3.6	2.8	64.4	74.71	5.9	48.13	5.1	85.6	40.3	17.0
1996	2.4	2.3	64.9	70.53	6.5	45.81	6.3	77.4	38.2	12.5
1995	1.5	2.1	65.1	66.22	4.8	43.10	5.4	70.4	37.0	8.5
1994	1.2	3.1	64.7	63.19	3.9	40.91	5.7	66.7	36.2	5.5

Sources: Smith Travel Research Annual HOST Study.

Source – Standard and Poor's Industry Surveys, Lodging and Gaming, August 2004

4. Econometric Model

This section formulates a stochastic long-run equilibrium model for the lodging industry where property managers simultaneously choose an action from a finite set of alternatives (do not enter, enter, stay, exit)[50]. The framework generates discrete controls i.e. endogenous do not enter, entry, continue and exit decisions from a combination of deterministic and stochastic observable factors like demand, excess capacity, price, brand affiliation, experience and private investment shocks. The private shocks in each period are drawn from a known distribution function (Logit). Firms make long-run forward looking decisions taking into account the effect -- a) its own past and future entry, stay and exit decisions b) current, past and anticipated

[50] We assume that each property is independently managed

decisions of its competitors and c) market uncertainty -- on current and future profits.

Before describing the elements of the model lets list out the notations used

t = time, takes on discrete values. $t \in T = \{1, 2.....\infty\}$

c = city

j = lodging property. $j \in J_c$ where $J_c = \{1, 2, ...N_c\}$ is the set of properties in

the market. The set N_c is assumed to be finite

s_{jt} = $(X_{jt}, \varepsilon_{jt})$ is the pairwise vector of observable and unobservable state

variables for property j at time t

X_{jt} = vector of variables that are common knowledge to all properties

X_t = vector of X_{jt}

d_t = vector of firm actions

S_t = market state vector = $(s_1^t, s_2^t, ... s_{Nc}^t)$

$S_{j-,t}$ = $(s_1^t, s_2^t, \ldots, s_{j-1}^t, s_{j+1}^t, .. s_{Nc}^t)$ is the state vector for the market excluding

property j

ε_{jt} = is a K dimension vector of ε_{jk}^t (one for each decision k), captures the real

valued private shock to property j's profit function. $\varepsilon_j^t \in R^k$ Each ε_{jk}^t is i.i.d. with Type I extreme value distribution with mean 0 and variance σ[51]

ε_t = is a $(K * N_c)*1$ vector of private knowledge of the firms in the market

[51] The i.i.d assumption allows us to use the Markov decision framework. Interested readers can refer to Rust (1987) for more details.

We define a market as a city-month pair[52]. There are N_c properties operating (making entry, exit or stay decisions) in city c at time t. If j indexes a property then $j \in J_c = \{1, 2, ..., N_c\}$. In each market all firms, even those that are non operational at time t, simultaneously decide if they want to stay out, enter, stay or exit the market. So that the model is well behaved we assume that per period profits are bounded from above for all possible decisions D where the set D is finite[53]. Therefore, a firm's set of choice alternatives is $D = \{0, 1, 2, 3\}$. We represent the decision of firm j at period t by the variable $d_{jt} \in D$ such that

$$d_{jt} \in D = \begin{cases} 0 & \text{if } j \text{ does not enter at time } t \\ 1 & \text{if } j \text{ enters at time } t \\ 2 & \text{if } j \text{ continues to stay at time } t \\ 3 & \text{if } j \text{ exits the market at time } t \end{cases}$$

Variables in X_t include -- number of properties of the same brand that operate in the market, property capacity, market level excess capacity, average maturity of market (average number of months that incumbent firms have been operating in the market), quality, excess capacity for properties of similar quality etc. The market maturity measure, proxies for early mover accumulated stock. If there is any advantage to early entry then we would expect the parameter associated with this measure to be negative and significant. In order to capture learning-by-doing effects, like Benkard (2004) we allow the per-period costs to be a function of time

[52] While the data contain information on zip codes and MSA associations for each property sparseness of the data and to avoid ad-hoc restriction of the competitive set, we chose city-month pair to be our market for the empirical analysis. The limitation of this approach is that all properties within a city however far apart they might be are viewed as being competitors.

[53] This implies that firm profits reduce as number of competitors increase in its market.

since entry[54]. Unobservable drivers like managerial ability, location and franchising etc are captured by private shock ε_{jt}.

Property *j*'s current period profit depends on X_t, its own private information ε_{jt}, and on the vector of decisions $d_{jt} \equiv (d_{0t}, d_{1t}, d_{2t}, d_{3t})$. Let vector $\boldsymbol{\Pi}_j(d_t, x_t, \varepsilon_{jt})$ be firm *j*'s current period profit function where evolution of (x_t, ε_t) follows a controlled Markov process with transition probability $p(x_{t+1},\varepsilon_{t+1} \mid d_t,x_t,\varepsilon_t)$. It is worth pointing out that while ε_{jt} is private knowledge its transition probability is common knowledge.

Each property manager maximizes his/her long-run expected discounted profits given by

$$E[\sum_{m=t}^{\infty} \Gamma^{m-t} \boldsymbol{\Pi}_j(d_m, x_m, \varepsilon_{jm}) \mid x_t, \varepsilon_{it})] \tag{1}$$

where $\Gamma \in (0, 1)$ is the discount factor. As in Rust (1997) assuming *additive separability* allows us to separate out the effect of private and public information on per period profits. This implies

$$\boldsymbol{\Pi}_j(d_m, x_m,\varepsilon_{jm}) = \boldsymbol{\Pi}_j(d_m, x_m) + \varepsilon_{jt}(d_{jt}) \tag{2}$$

Conditional independence allows us to independently model transition probability p(.|.) i.e. the model that captures the evolution of the state space is independent for private and public information[55]. In other words given firms' decisions in period *t* and the independently distributed private information across firms implies

$$p(x_{t+1},\varepsilon_{t+1} \mid d_t,x_t,\varepsilon_t) = p_\varepsilon(\varepsilon_{t+1})\, f(x_{t+1} \mid d_t, x_t) \tag{3}$$

$$p_\varepsilon(\varepsilon_t) = \prod_{j=1}^{Nc} g_j(\varepsilon_{jt})$$

[54] Our specification captures one of the many elements of learning-by-doing i.e. cost efficiencies.

[55] This assumption implies that the private information variables do not affect the transition of common knowledge variables and private information variables are independently and identically distributed over time.

where $g_j(.)$ is a continuous density function and f (.|.) is the p.d.f. of transition probability of the observable/common knowledge state variables. Like Aguirregabiria and Mira (2002b) we assume that the common knowledge variables are discrete with finite support.

If the property does not enter the market it earns zero profit in the current time period. Entry in current period results in no revenue that period, but requires a single period sunk cost of entry that is linear quadratic in the capacity of the property[56] i.e

$$\Pi_{jt}(d_{j1t}, x_{1t}, \varepsilon_{1jt}) = \gamma_1 Cap_{jt} + \gamma_2 Cap_{jt}^2 + \varepsilon_{jt}(d_{1jt}) \quad (4)$$

Decision to stay in the market post entry results in a per period profit that is a function of current period demand (D_{jt}), price (ADR_{jt}), own excess capacity ($ECap_{jt}$), market level excess capacity ($MECap_t$), number of properties a) in the market N_t and b) of the same quality as property *j* (N_{tq_j}) c) of the same brand as *j* (N_{tb_j}), quality (Q_J). The market, within quality tier and within brand variables capture the strategic interactions. In order to capture the effects of learning-by-doing we model the per period costs post entry as a function of time since entry (TSE_{jt}) and current capacity. More specifically conditional on all other firms playing their optimal strategies

$$\Pi_{jt}(d_{2jt},x_{2t},\varepsilon_{2jt}) = \begin{array}{l} \beta_{0b_j} + \beta_1 ADR_{jt} + \beta_2 D_{jt} + \beta_3 N_t + \beta_4 N_{tb_j} + \beta_5 N_{tq_j} \\ -\beta_6 TSE_{jt} * ECap_{jt} + \beta_7 (TSE_{jt} * ECap_{jt})^2 \\ -\beta_8 TSE_{jt} * Q_j * MECap_t + \beta_9 (TSE_{jt} * Q_j * MECap_t)^2 \\ -\beta_{10} TSE_{jt} * Cap_{jt} + \beta_{11} (TSE_{jt} * Cap_{jt})^2 \\ -\beta_{12} TSE_{jt} * Q_j * MCap_t + \beta_{13} (TSE_{jt} * Q_j * MCap_t)^2 \end{array} + \varepsilon_{jt}(d_{2jt}) \quad (5)$$

[56] We assume that entry costs are completely incurred in the period prior to actual entry in the data. While we do not model this ourselves, another specification for entry costs could account for market density since its quite conceivable that scarcity of land can lead to higher entry costs for late entrants.

If an incumbent property j decides to exit then it obtains a scrap value for the property that is a function of the brand, quality, time since entry and existing capacity.

$$\Pi_{jt}(d_{3jt},x_{3t},\varepsilon_{3jt})= \mu_0 + \mu_1 TSE_{jt} * Q_j * I_{b_j} * Cap_{jt} + \mu_2 (TSE_{jt} * Q_j * I_{b_j} * Cap_{jt})^2 + \varepsilon_{jt}(d_{3jt}) \tag{6}$$

The vector of structural parameters of the model is $\Theta = [\alpha, \beta, \mu]$.

A Markov structure for the game being played between the lodging properties implies that when a firm is presented with the same state vector at different time periods s_{jt_1} and s_{jt_2} it will take the same decision in both time periods. Hence we can conveniently drop the time subscript.

Let $\sigma = \{\sigma_j(x, \varepsilon_j)\}$ be a set of strategy functions or decision rules, then associated with a set of strategy functions σ we can define a set of conditional choice probabilities $P_j^{\sigma}(d_j \mid X)$ i.e. the expected behavior of the firm j as viewed by its competitors in its market when the firm j follows $\sigma_j(x, \varepsilon_j)$. The semi-conditional profit functions (Harsanyi, 1995) $\Pi_j^{\sigma}(d_j \mid X)$, the expected payoff for firm j if it plays strategy d_j and its competitors play strategy d_{j-} in σ is given by

$$\Pi_j^{\sigma}(d_j \mid X_t) = \sum_{d_{j-}} \left[\prod_{j-} P_j^{\sigma}(d_j \mid X) \right] \Pi_j(d_j, d_{j-}, X_t) \tag{8}$$

where $\Pi_j(d_j, d_{j-}, X)$ is the conditional payoff.

The Bellman equation principle governed *value function* for firm j if firm j and its competitors behave optimally in the current and in all future periods is given by

$$\begin{aligned}\Xi^{\sigma}_{jt}(d_{jt} \mid X_t) &= \max_{d_j \in D}\left[\Pi^{\sigma}_{jt}(d_{jt}, X_t)\right] + \varepsilon_{jt}(d_{jt}) \\ &+ \Gamma \sum_{t+}\left[\int \Xi^{\sigma}_{jt+}(d_{jt+}, X_{t+}) g_j(\varepsilon_{jt+}) d\varepsilon_{jt+}\right] f^{\sigma}_j(X_{t+} \mid X_t, d_{jt})\end{aligned} \tag{9}$$

Where $f^{\sigma}_j(X_{t+} \mid X_t, d_{jt})$ is the transition probability of X conditional on firm *j* choosing d_{jt} and the other firms behaving according to σ. The model that captures the evolution of the common knowledge state space is given by

$$f^{\sigma}_j(X_{t+} \mid X_t, d_{jt}) = \Pi^{\sigma}_j(d_j \mid X_t) = \sum_{d_{j-,t}}\left[\prod_{j-} P^{\sigma}_j(d_j \mid X)\right] f(X_{t+} \mid d_{jt}, d_{j-,t} X_t) \tag{10}$$

Conditional independence and independent private values allows us to integrate over the distribution of the private values to generate the *integrated Bellman equation* given by

$$\Xi^{\sigma}_j(X_t) = \int \max_{d_j \in D}\left[\Pi^{\sigma}_{jt}(d_{jt}, X_t) + \varepsilon_{jt}(d_{jt}) + \Gamma \sum_{X_{t+}} \Xi^{\sigma}_j(X_{t+}) f^{\sigma}_j(X_{t+} \mid X_t, d_{jt})\right] g_j(d\varepsilon_{jt}) \tag{11}$$

Note that equation 11, is a contraction mapping in the space of value functions. Aguirregabiria and Mira (2002b) prove that for a contraction mapping of the form in (11) there is a unique function $\Xi^{\sigma}_j(X_t)$ that solves the above for a given σ.

5. The Equilibrium Concept and Estimation

Our long-run equilibrium specification does away with the limitations of previous two period/static models as explained in the previous sections. However the computation requirements for such equilibria can be quite prohibitive (Benkard, 2004) since the tests for optimality require computing equilibria over all possible actions for each time period for all possible states and for all firms. Rather than an approach that requires a repeated computation of equilibria, we use a two-step estimator like that of Hotz and Miller (1993) for a single agent case and Benkard (2004) and Aguirregabiria and Mira (2002a, 2002b) for multi-agent dynamic equilibria.

In the first step, we estimate the parameters of the model that govern the transition probabilities of the observed (public) and unobserved (private) state variables via a nonparametric regression of the observed (in the data) decisions (entry, exit, stay and investments/costs) on the explanatory variables of the first order Markov process in equation 10. An assumption that facilitates recovery of the structural parameters of decision makers' beliefs at each point in time is that all agents (property managers) have correct common beliefs about the factors of the environment and respond to the best response of other agents.

The second step involves estimating the remaining structural parameters by matching the observed decisions (in the data) with the appropriate optimality conditions. This requires the observed decision at each state for each property to be weakly preferred to all feasible alternative decisions resulting in a system of equations for each property for each time period. The indifferent alternative is not observed but is inferred from the observed choices. Identification is therefore reduced to the existence of a unique solution to the equation system.

Before we get to the estimation algorithm lets us characterize the equilibrium concept for the model described in the previous section. Given the Markov perfect equilibrium concept, each firm chooses an equilibrium strategy $\sigma_j^*(X,\varepsilon_j)$ such that it is the best response to its competitor's optimal strategy. Hence

$$\sigma_j^*(X_t,\varepsilon_{jt}) = \underset{d_j \in D}{Arg\max}\left[\Pi_{jt}^{\sigma}(d_{jt},X_t) + \varepsilon_{jt}(d_{jt}) + \Gamma\sum_{X_{t+}}\Xi_j^{\sigma}(X_{t+})f_j^{\sigma}(X_{t+} \mid X_t,d_{jt})\right]$$

(12)

Note that the best response is a function of the choice probabilities. Therefore the Markov perfect equilibria can be expressed as a contraction mapping in the probability space of firm strategies. This feature offers computational convenience and makes the equilibrium probabilities (not equilibrium itself) a fixed-point contraction mapping. Hence reformulating our contraction mapping as a mapping in the probability space and rewriting the integrated Bellman equation in terms of functions of $P*$ a vector equilibrium probabilities for all firms in a market yields

$$\Psi_j(d_{jt} \mid X_t;P) = \int I\left\{ d_{jt} = \underset{d_j \in D}{Arg\max}\left[\begin{array}{l}\Pi_{jt}^{P}(d_{jt},X_t) + \varepsilon_{jt}(d_{jt}) \\ +\Gamma\sum_{X_{t+}}\Xi_j(X_{t+},P)f_j^{\sigma}(X_{t+} \mid X_t,d_{jt})\end{array}\right]\right\} g_j(\varepsilon_j)d\varepsilon_j$$

(13)

Note, constructing the mapping in the probability space allows us to take the future decisions as given thereby significantly reducing computational complexity since we don't have to calculate the value functions for all future states as is done in Rust (1997). Assuming that $g(.)$ is i.i.d Type 1 Gumbel yields the multinomial Logit expression for $\Psi(\bullet)$.

6. Estimation and Results

To estimate the structural parameters of our model we use a nested pseudo likelihood (NPL) estimator. The NPL method is a recursive extension of the two-step pseudo likelihood estimator (PML) that maximizes the number of evaluations of $\Psi_j(d_{jt} \mid X_t; P_t)$ for different probability vectors *P*. The pseudo-likelihood function is given by

$$PMLE(\Theta, P) = \frac{1}{C}\sum_{c=1}^{C}\sum_{t=1}^{T}\sum_{j=1}^{Nc}\ln\left(\Psi_j(d_{jct} \mid X_{ct}; P, \Theta)\right) \tag{14}$$

The estimation procedure starts with P_0 , an initial guess of the vector of players' choice probabilities. Given P_0, NPL generates a sequence of estimators such that

$$\begin{aligned} \Theta_k &= \arg\max(PMLE(\Theta, P_{k-1})) \\ P_k &= \Psi(\Theta_k, P_{k-1}) \end{aligned} \tag{15}$$

The NPL is a fixed point in the limit of this sequence[57]. NPL is more efficient than PML and therefore more efficient than the two-step PML.

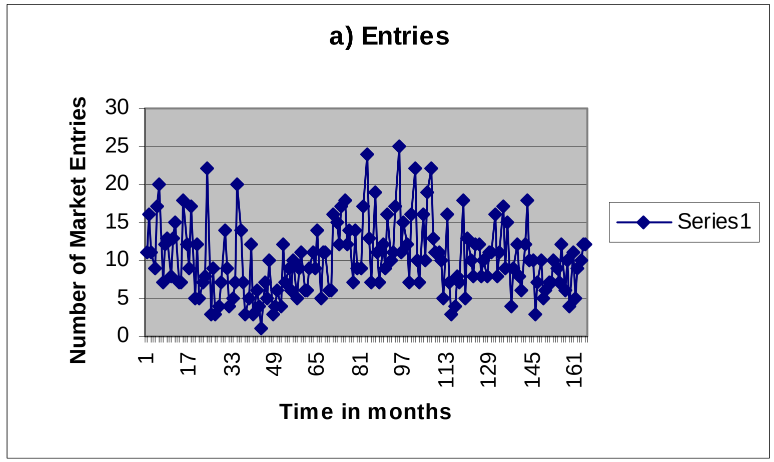
The empirical analysis involves estimation of five different models including the proposed model. In order to compare the appropriateness of our long-run dynamic model, we start by estimating a static model. Model 1 is a static model where we force the discount factor to be zero. This results in firms making decisions that maximize only current period profits and not the expected discounted current period profits. Model 2, is a MPNE based dynamic model with the added constraint that firms are homogenous i.e. without observed heterogeneity that stem from brand fixed effects and quality dummy. Model 3, relaxes the homogeneity assumption and allows observed heterogeneity. Note that while we account for observed heterogeneity the model still assumes symmetric Markov perfect equilibria[58]. Model 4, captures the role of learning-by-doing effects on firm costs. Model 5 is the

[57] Please refer to Aguirregabiria and Mira (2002) for detailed explanation of how in the limit NPL satisfies Brower's theorem and guarantees the existence of at least one fixed point.
[58] To account for asymmetric equilibria we would have to allow for mixed strategies which adds more complexity to the modeling framework. Furthermore existence conditions for such equilibria are not clear and beyond the scope of this study.

full model proposed in previous section accounts for firm heterogeneity, learning-by-doing effects and role of excess capacity on firm decisions. Tables 3.4 a) and 3.4 b) illustrate the explanatory variables included in each of the models.

The results of the empirical analysis is shown in Tables 3.5 a) and 3.5 b) respectively. Focusing on common parameter estimates of Model 1 and others models, we observe that by and large Model 1 over-estimates the factors that drive firm decisions. As shown in Table 3.6 based on BIC model selection criteria the Model 1 has worst statistical fit when compared to it dynamic counterparts. Within-sample predictions using a hit rate statistic also demonstrate the significant improvement in predictions by accounting for long-run dynamic effects.

The empirical findings of this essay therefore provide support for the appropriateness of a dynamic framework to study entry, stay and exit decisions in our data. Accounting for observed heterogeneity improves the fit of Model 2. Significant differences in the magnitude and signs of the brand fixed effects indicate a high degree of variation among firms. This could be in part because of our choice of brands for the empirical analysis where for the purpose of accounting for vertical and horizontal differentiation we choose large share brands across different sub-tiers of the Midscale sector.



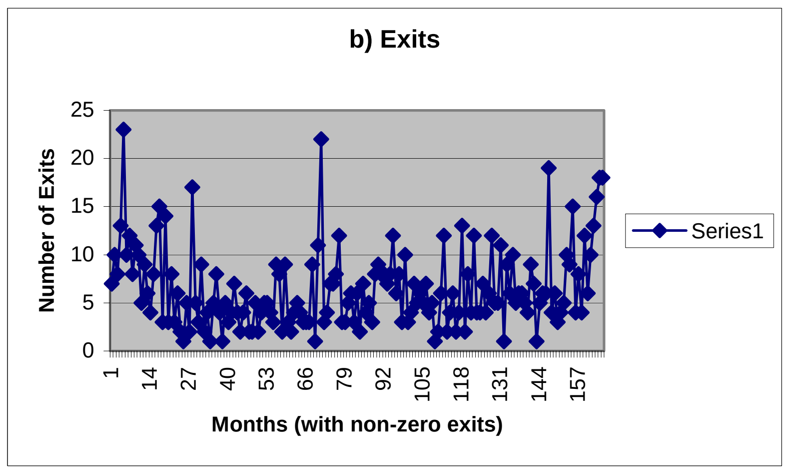


Figure 3.1 – Market Level Entry-Exit-Decisions

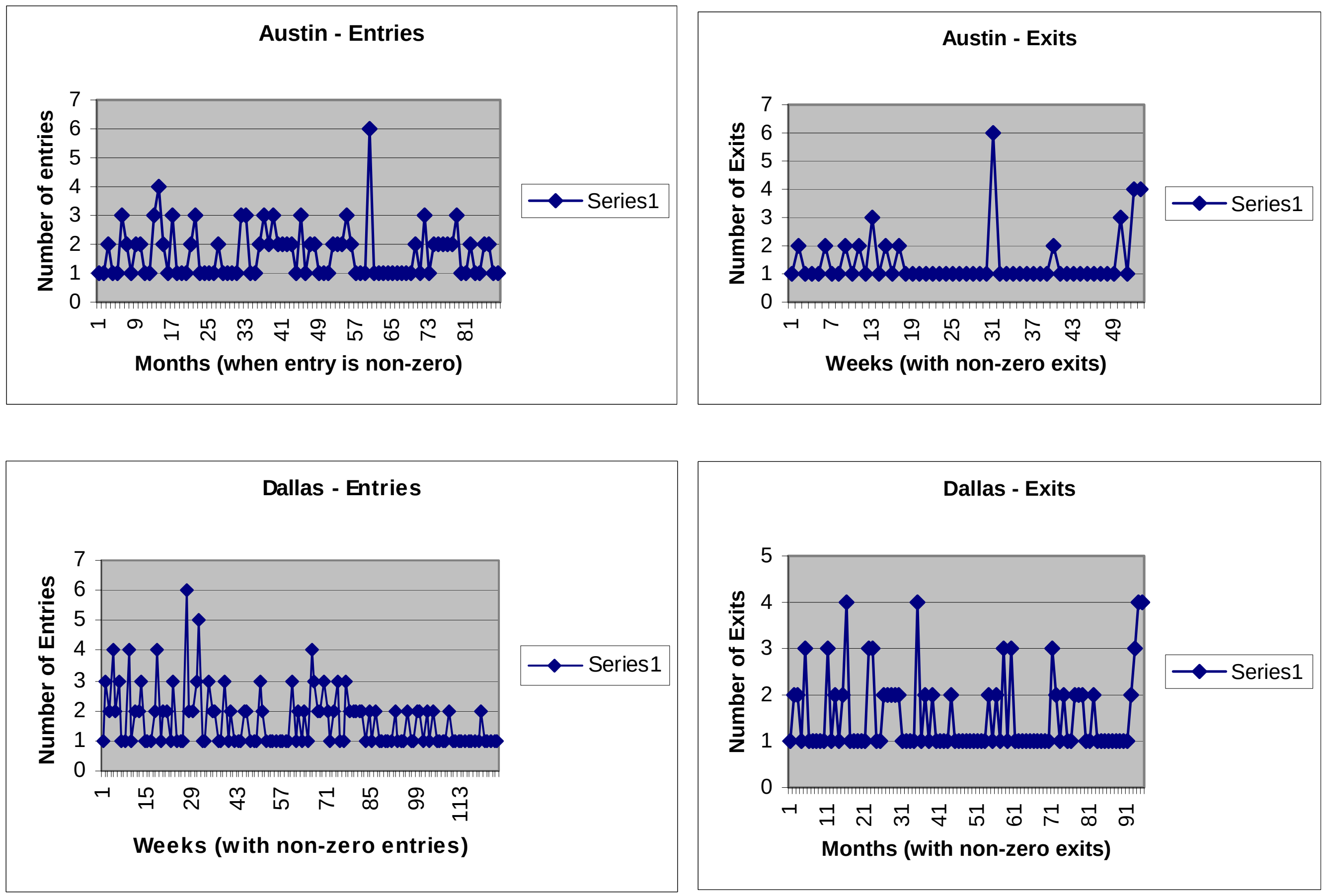


Figure 3.2 – City Specific Entry-Exit Decisions

TABLE 3.3 - Descriptive Statistics Of Estimation Sample

Variable	Mean	Std Dev	Min	Max
Capacity	102.93	44.44	32.00	276.00
Price (ADR)	35.38	31.08	0	205.33
Number of active firms	199.64	53.09	128.00	259.00
Number of active firms of same brand	8.13	4.72	1.00	18.00
Number of active firms of same quality	114.67	34.28	62.00	151.00
Excess Capacity (property)	23.11	22.52	8.60	95.53
Excess Capacity (market)	21.53	21.31	0	75.89
Months since entry	119.06	182.64	0	1734.00
Average months since entry (market)	93.12	33.59	34.64	185.74
Average months since entry (same quality)	93.91	39.56	20.09	198.01

TABLE 3.4 (a) - Effects

Variables	***Structural Parameters***	***Model 1*** Static model	***Model 2*** Without Observed Firm Heterogeneity	***Model 3*** With Observed Firm Heterogeneity	***Model 4*** Model 2 + Learning-by-Doing Efficiency	***Model 5*** Model 3 + Excess Capacity
Entry Variables	Capacity (γ_1)	√	√	√	√	√
	Capacity² (γ_2)	√	√	√	√	√
Stay Variables	Brand 1 (β_{0b_1})		-	√	√	√
	Brand 2 (β_{0b_2})		-	√	√	√
	Brand 3 (β_{0b_3})		-	√	√	√
	Brand 4 (β_{0b_4})		-	√	√	√
	Price (β_1)	√	√	√	√	√
	Demand (β_2)	√	√	√	√	√
	No. of Active Firms (β_3)	√	√	√	√	√
	No. of Firms of same Brand (β_4)	-	-	√	√	√
	Number of Firms of same quality (β_5)	-	-	√	√	√
	Experience weighted excess capacity of property (β_6)	-	-	-	-	√
	(Experience weighted excess capacity of property)² (β_7)	-	-	-	-	√

TABLE 3.4 (b) - Effects (continued)

Variables	***Structural Parameters***	***Model 1*** Static model	***Model 2*** Without Observed Firm Heterogeneity	***Model 3*** With Observed Firm Heterogeneity	***Model 4*** Model 2 + Learning-by-Doing Efficiency	***Model 5*** Model 3 + Excess Capacity
	Experience and quality weighted excess capacity of market (β_8)	-	-			√
	(Experience weighted excess capacity of market)^2 (β_9)	-	-			√
	(Experience weighted capacity of property) (β_{10})	√	√	√	√	√
	(Experience weighted capacity of property)^2 (β_{11})	√	√	√	√	√
	(Experience and quality weighted capacity of market) β_{12}	-	-	√	√	√
	(Experience and quality weighted capacity of market)^2 (β_{13})	-	-	√	√	.√
Exit Variables	(Experience, quality and brand weighted capacity of property) μ_1	√	√	√	√	√
	(Experience, quality and brand weighted capacity of property)^2 (μ_2)	√	√	√	√	. √
	Fixed effect (μ_0)	√	√	√	√	√

TABLE 3.5 (a) - Estimation Results

Variables	***Structural Parameters***	***Model 1*** Static model	***Model 2*** Without Observed Firm Heterogeneity	***Model 3*** With Observed Firm Heterogeneity	***Model 4*** Model 2 + Learning-by-Doing Efficiency	***Model 5*** Model 3 + Excess Capacity
Entry Variables	Capacity (γ_1)	5.09	-6.78	-5.19	-3.87	-2.04
	Capacity^2 (γ_2)	-2.19	.027	1.34	2.65	1.77
Stay Variables	Brand 1 (β_{0b_1})		-	9.32	11.59	12.38
	Brand 2 (β_{0b_2})		-	13.41	18.67	15.09
	Brand 3 (β_{0b_3})		-	2.54	4.23	11.52
	Brand 4 (β_{0b_4})		-	6.98	4.36	3.94
	Price (β_1)	23.08	18.91	21.44	19.87	7.73
	Demand (β_2)	28.94	19.34	18.39	16.95	13.78
	No. of Active Firms (β_3)	-5.77	-3.71	-2.88	-3.48	-3.09
	No. of Firms of same Brand (β_4)	-	-	-1.11	-2.08	-2.85
	Number of Firms of same quality (β_5)	-	-	-4.55	-9.37	-8.60
	Experience weighted excess capacity of property (β_6)	-	-	-	-	4.29
	(Experience weighted excess capacity of property)^2 (β_7)	-	-	-	-	1.36**

** implies statistically not significant

TABLE 3.5 (b) - Estimation Results (continued)

Variables	***Structural Parameters***	***Model 1*** Static model	***Model 2*** Without Observed Firm Heterogeneity	***Model 3*** With Observed Firm Heterogeneity	***Model 4*** Model 2 + Learning-by-Doing Efficiency	***Model 5*** Model 3 + Excess Capacity
	Experience and quality weighted excess capacity of market (β_8)	-	-			1.01
	(Experience weighted excess capacity of market)^2 (β_9)	-	-			.633
	(Experience weighted capacity of property) (β_{10})	5.79	4.07	3.87	2.50	3.13
	(Experience weighted capacity of property)^2 (β_{11})	1.008**	1.20**	3.71**	3.54	2.001
	(Experience and quality weighted capacity of market) β_{12}	-	-	2.60	1.87	2.903
	(Experience and quality weighted capacity of market)^2 (β_{13})	-	-	.409	.005**	.0866**
Exit Variables	(Experience, quality and brand weighted capacity of property) μ_1	17.40	16.41	11.38	13.21	9.97
	(Experience, quality and brand weighted capacity of property)^2 (μ_2)	5.16	3.80**	2.04	.833	.234
	Fixed effect (μ_0)	26.34	18.34	9.30	4.31	4.054

** implies statistically not significant

Table 3.6 - Model Selection Criteria

Model Selection Criteria	***Model 1*** **Static model**	***Model 2*** **Without Observed Firm Heterogeneity**	***Model 3*** **With Observed Firm Heterogeneity**	***Model 4*** **Model 2 + Learning-by-Doing Efficiency**	***Model 5*** **Model 3 + Excess Capacity**
BIC	-36,996	-32,184	-28,691	-23,455	-21,743
Hit Rate	.374	.51	.57	.612	.673

Model 4, provides empirical support for learning-by-doing effects on firm decisions. The sign of the first order and second order cost variables shows significant cost efficiencies as a result of learning. The signs of these parameters suggest that with experience property managers become more efficient in containing operating costs of capital. Finally Model 5 i.e. our proposed model provides significant improvement over Model 1 and incremental improvements in fit over its predecessor models. As demonstrated in Conlin and Kadiyali (2000) we also find a significant role of excess capacity both at the market and within quality tier, on firm entry decisions. The negative sign suggests that market excess capacity can deter future entry. This effect is stronger within the same quality tier than at the market level[59] providing evidence of greater competitive interactions between firms belonging to same quality tier than across different tiers.

[59] Note that excess capacity in this paper is treated as being exogenous. Realizing that excess capacity deters future entry and operating costs of excess capacity will reduce over time, incumbent firms might act strategically and invest in excess capacity. While endogeinity in capacity choice is not account for in our model, it is a worthwhile area for future extension of this paper.

7. Conclusions and Directions for Future Research

This paper presents empirical dynamic discrete game-theoretic model of entry, exit and stay for the lodging industry in Texas. The proposed model presents a unified model of numerous factors that affect and are affected by competitive entry, stay and exit decisions. Unlike previous reduced form static/two period models in this essay a long-run equilibrium model is presented. Based on non-nested model selection criteria (BIC) our empirical results demonstrate that a long-run dynamic equilibrium model better describes the behavior of firms in our data than single period/static models[60].

Extensions to this essay could include a) multi-segment comparisons b) correction for price and/or capacity endogeneity c) accounting for strategic excess capacity decisions and d) accounting for possible correlations in the private shocks across the discrete decisions.

To summarize, we make a case for the appropriateness of dynamic game-theoretic modeling frameworks to study discrete decisions for example entry/exit decisions in markets with large entry costs and irreversible investments. While entry, exit and stay decisions is the main focus of this essay, the modeling framework can be extended to account for price dynamics. Entry deterrence strategies like limit pricing (Masson and Shaanan, 1986) and excess capacity (Conlin and Kadiyali, 2000) can be better explained using such integrated dynamic models since these models account for anticipatory behavior not captured in static models.

[60] The proposed model also outperforms a static model on prediction task i.e. hit rate criteria. Please contact the author for detailed information on the hit rate results and calculation procedure.

REFERENCES

Aguirregabiria, V., and P. Mira, (2002a). "Sequential Simulated-Based Estimation of Dynamic Discrete Games," mimeo, Boston University, 2002.

Aguirregabiria, V., and P. Mira, (2002b). "Swapping the nested fixed point algorithm - A class of estimators for Markov decision models," *Econometrica*, 70(4), 1519-43.

Bain, Joe S. (1956). "Barriers to New Competition."Cambridge, Mass.: Harvard University Press.

Benkard, L., (2004). "A Dynamic Analysis of the Market for Wide-bodied Commercial Aircraft," *Review of Economic Studies*, forthcoming.

Berry, S., (1992). "Estimation of a Model of Entry in the Airline Industry," *Econometric*a, 1992, 889-918.

Berry, S., and J. Waldfogel, (1999)."Free Entry and Social Inefficiency in Radio Broadcasting," *RAND Journal of Economics*, 1999, 397-420.

Borenstein, S., and J. Netz, (1999). "Why Do All the Flights Leave at 8 a.m.? Competition and Departure Time Differentiation in Airline Markets," *International Journal of Industrial Organization*, 1999, 611-640.

Bresnahan, T., (1992). "Sutton's Sunk Costs and Market Structure Price Competition, Advertising, and the Evolution of Concentration Review Article," *RAND Journal of Economics*, 1992, 137-52.

Bresnahan, T., and P. Reiss, (1990). "Entry in Monopoly Markets," *Review of Economic Studies*, 1990, 531-53.

Bresnahan, T., and P. C. Reiss, (1991). "Econometric Models of Discrete Games," *Journal of Econometrics*, 1991, 57-81.

Bresnahan, T., and P. Reiss, (1991)"Entry and Competition in Concentrated Markets," *Journal of Political Econom*y, 1991, 977-1009.

Chandler, A. D., (1990). "*Scale and Scope : The Dynamics of Industrial Capitalism*." Cambridge, MA, Harvard University Press.

Conlin, M., Kadiyali, V., (2000). "Entry Deterring Capacity in the Texas Lodging Industry." Working paper

Dasgupta, P. And Stiglitz, J., (1988). "Learning-By-Doing, Market Structure And Industrial And Trade Policies", *Oxford Economic Papers*, 40, 246-268.

Davis, P. J., (2002). "Entry, Cannibalization and Bankruptcy in the U.S. Motion Picture Exhibition Market," manuscript, London School of Economics, 2002.

Dixit, A., Pindyck, R. S., (1994). "Investment under Uncertainty," Princeton University Press, Princeton, New Jersey, 1994.

Dolan, Robert J. and Jeuland, Abel P. (1981). "Experience Curves and Dynamic Demand Models: Implications for Optimal Pricing Strategies." *Journal of Marketing*, *45*(1), pp. 52.

Doraszelski, U. & Satterthwaite, M. (2001). Markov-perfect industry dynamics: Existence and uniqueness, Working paper, Northwestern University, Evanston.

-------------, & Besanko, D., (2004). "Capacity Dynamics and Endogenous Asymmetries in Firm Size," *Rand Journal of Economics*, Vol. 35.

Dube', J.P, Hitsch J. Gunter, and Puneet Manchanda, (2003). "An Empirical Model of Advertising Dynamics," Working paper.

Dutton, J. and Thomas, A. (1984). "Treating progress functions as managerial Technology," *Academy of Management Review* 9: 235-247.

Einav, L., (2004) "Not All Rivals Look Alike: Estimating an Equilibrium Model of the Release Date Timing Game," mimeo, Stanford University, 2004.

Eliashberg, J., Chatterjee, R., (1985). "Analytical Models of Competition with Implications for Marketing: Issues, Findings, and Outlook" *Journal of Marketing Research,* Vol. 22, August 1985,

-------------, Jeuland, A., (1986). “The Impact of Competitive Entry in a Developing Market upon Dynamic Pricing Strategies”, *Marketing Science*, Vol. 5, No. 1, Winter 1986, pp. 20-36.

Ellickson, P. (2003) "Competition in the Supermarket Industry: Sunk Costs and Market Structure," manuscript, Department of Economics, Duke University.

Ellison, Glenn, and Sara Fisher Ellison, (2000), “Strategic Entry Deterrence and the Behavior of Pharmaceutical Incumbents Prior to Patent Expiration,” mimeo, MIT Department of Economics.

Engers, M., and S. Stern (2002) “Long-Term Care and Family Bargaining,” International Economic Review, 43, 73-114

Ericson, R., and A. Pakes (1995) “Markov-Perfect industry dynamics: A framework for empirical work”, *Review of Economic Studies*, 62, 53-82.

Fudenberg, D. and Tirole, J. (1983). “Learning-by-doing and market performance,” *Bell Journal of Economics* 14.

Goettler, R. L., and R. Shachar, (2001) “Spatial Competition in the Network Television Industry,” *RAND Journal of Economics*, 2001, 624-656.

Greenwald, B. , Stiglitz, J., (1990). “Asymmetric Information and the New Theory of the Firm: Financial Constraints and Risk Behavior,” *American Economic Review*, 80(2), May 1990, pp. 160-65.

Hitsch, G. J., (2003) “Estimating a Bayesian Learning Model of Product Launch and Product Exit,” mimeo, University of Chicago, 2001.

Gourieroux, C., and A. Monfort (1995) “Statistics and Econometric Models: Volume I”, Cambridge University Press.

Harsanyi, J. (1995) “Games with incomplete information,” *American Economic Review*, 85, 291-303.

Heckman J. (1978) “Dummy endogenous variables in a simultaneous equation system”, *Econometrica*, 46, 931-959.

Heckman, J. (1981) “The incidental parameters problem and the problem of initial conditions in estimating a discrete time - discrete data stochastic process,” in C. Manski and D. McFadden (eds.), Structural Analysis of Discrete Data with Econometric Applications. MIT Press.

Hotz, J., and R.A. Miller (1993) “Conditional choice probabilities and the estimation of dynamic models”, *Review of Economic Studies*, 60, 497-529.

Hotz, J., R.A. Miller, S. Sanders, and J. Smith (1994) ”A simulation estimator for dynamic models of discrete choice,” *Review of Economic Studies*, 61.

Hopenhayn, (1992), “Entry, Exit, and Firm Dynamics in Long Run Equilibrium,” *Econometrica*, 60(2): 1127-1150.

Jacobson, Robert and David A. Aaker (1985), "Is Market Share All That It's Cracked Up To Be?," *Journal of Marketing*, 49 (Fall), 11 -22.

----- (1988), "Distinguishing Among Competing Theories of the Market Share Effect," *Journal of Marketing*, 52 (October), 68-80.

----- (1990), "Unobservable Effects and Business Performance," *Marketing Science*, 9 (Winter), 74-85.

Jovanovic, B. (1989) “Observable implications of models with multiple equilibria”, *Econometrica*, 57, 1431-1437.

-----------, MacDonald, G., (1994). "The Life-Cycle of a Competitive Industry," NBER Reprints 1894.

Kadiyali, V., (1996) “Entry, Its Deterrence, and Its Accommodation: A Study of the U.S. Photographic Film Industry, *Rand Journal Of Economics*, Vol. 27, No. 3.

----------, K. Sudhir and Rao, Vithala R., (2001). “Structural Analysis of Competitive Behavior: New Empirical Industrial Organization Methods in Marketing.” *International Journal of Research in Marketing,* Vol. 18, No. 1-2, pp 161-186.

Lieberman, M. (1987), "Excess Capacity as a Barrier to Entry: An Empirical Appraisal," *The Journal of Industrial Economics*, 35, 607-627.

-----------, D.B. Montgomery, (1998). "First-Mover Advantages", *Strategic Management Journal*, Vol. 9, 1988, pp. 41-58.

-----------, M.B. Lieberman, and D.B. Montgomery, "First-mover (Dis)Advantages: Retrospective and Link with the Resource-Based View", *Strategic Management Journal*, Vol. 19, 1998, pp. 1111-1125.

Mankiw, G. and M. Whinston, (1986). Free entry and social inefficiency, *Rand Journal of Economics*, 17, 48-58.

Masson, R. and Shaanan, J. (1986), "Excess Capacity and Limit Pricing: An Empirical Test," *Economica*, 53, 365-378.

Mazzeo, M. (2002). "Product Choice and Oligopoly Market Structure," *Rand Journal of Economics*, Summer 2002

McFadden, D., and W. Newey (1994) "Large Sample Estimation and Hypothesis Testing," in R. E. Engle and McFadden (eds.) Handbook of Econometrics Volume 4, North-Holland.

McGahan, A. & Porter, M. (1997). How much does industry matter, really?, *Strategic Management Journal* 18: 15–30.

Netz, J. and B. Taylor (2002) "Maximum or minimum differentiation? Location patterns or retail outlets," Review of Economics and Statistics, 84(10, 162-175.

Pakes, A,.(2001). "A Framework for Dynamic Analysis in I.O.," NBER WP no. 8024, 2001.

Pakes, A. and Ericson, R., (1998). "Empirical Implications of Alternative Models of Firm Dynamics," *Journal of Economic Theory*, vol. 79, no. 1, pp. 1-46.

Pakes, A., M. Ostrovsky, and S. Berry, (2003). "Simple Estimators for the

Parameters of Discrete Dynamic Games (with Entry / Exit Examples)," mimeo, Harvard University, 2003.

Pakes, A. and P. McGuire, (1994). "Computing Markov-Perfect Nash Equilibrium: Empirical Implications of a Dynamic Model," *RAND Journal of Economic,* 1994, 555-589.

Pakes, A. and P. McGuire, (1995). "Empirical Implications of Alternative Models of Firm Dynamics," *Journal of Economic Theory*, 1995, 53-82.

Pakes, A. and P. McGuire (2002) "Stochastic algorithms for dynamic models: Markov Perfect equilibrium and the curse of dimensionality," *Econometrica*, forthcoming.

Pesendorfer, M. and Schmidt-Dengler (2003) "Identification and estimation of dynamic games," London School of Economics Working Paper.

Prescott, E. C., and M. Visscher, (1977). "Sequential Location among Firms with Foresight," *Bell Journal of Economics*, 1977, 378-393.

Rao, R. and Bass, F. M., (1985) "Competition, Strategy and Price Dynamics: A Theoretical and Empirical Investigation," *Journal of Marketing Research*, Special Issue on Competition, XXII (3), (August), 283-296.

Reiss, P., Wolak, F., (2002). "Structural Econometric Modeling: Rationales and Examples from Industrial Organization", forthcoming *Handbook of Econometrics*, Vol 4.

Rust, J. (1994) "Estimation of dynamic structural models, problems and prospects: discrete decision processes", in C. Sims (ed.) Advances in Econometrics. Sixth World Congress, Cambridge University Press.

Saloner, G. (1987). "Cournot duopoly with two production periods," *Journal of Economic Theory* 42(1): 183–187.

Scott-Morton, F., (1999). "Entry Decisions in the Generic Pharmaceutical Industry," *Rand Journal of Economics*, 1999, 421-440.

Shaked, Avner and John Sutton, (1983), "Natural Oligopolies," *Econometrica*, vol. 51, pp. 1469-1484.

Seim, K., (2003). "An Empirical Model of Firm Entry with Endogenous Product-Type Choices," mimeo, Stanford University.

Sinclair G., Klepper S., Cohen W., (2000). "Cost Reduction In A Large Specialty Chemicals Producer" *Management Science,* Vol. 46, No. 1, January 2000 29.

Spence, A. M., (1981). "The learning curve and competition," *Bell Journal of Economic*s 12.

Stavins, J., (1995). "Model Entry and Exit in a Differentiated-Product Industry: The Personal Computer Market," *The Review of Economics and Statistics*, 1995, 571-584.

Sweeting, A., (2002). "Music Variety, Station Listenership and Station Ownership in the Radio Industry," mimeo, MIT.

Sutton, J., (1991). *Sunk Costs and Market Structur*e, MIT Press, 1991, Chapters 1-2.

Szymanski, D. M., Bharadwaj, S., Varadarajan, P., (1991). "An Analysis Of The Market Share-Profitability Relationship," Journal of Marketing, 0022-2429, July 1, 1993, Vol. 57, Issue 3

Tamer, E., (2003). "Incomplete Simultaneous Discrete Response Model with Multiple Equilibria," *Review of Economic Studies*, 2003, 147-165.